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Nesting in the Clouds: Evaluating and Predicting Sea Turtle Nesting Beach Parameters from Lidar Data

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Abstract

Humans' desire for knowledge regarding animal species and their interactions with the natural world have spurred centuries of studies. The relatively new development of remote sensing systems using satellite or aircraft-borne sensors has opened up a wide field of research, which unfortunately largely remains dependent on coarse-scale image spatial resolution, particularly for habitat modeling. For habitat-specialized species, such data may not be sufficient to successfully capture the nuances of their preferred areas. Of particular concern are those species for which topographic feature attributes are a main limiting factor for habitat use. Coarse spatial resolution data can smooth over details that may be essential for habitat characterization.

Three studies focusing on sea turtle nesting beaches were completed to serve as an example of how topography can be a main deciding factor for certain species. Light Detection and Ranging (LiDAR) data were used to illustrate that fine spatial scale data can provide information not readily captured by either field work or coarser spatial scale sources. The variables extracted from the LiDAR data could successfully model nesting density for loggerhead (*Caretta caretta*), green (*Chelonia mydas*), and leatherback (*Dermochelys coriacea*) sea turtle species using morphological beach characteristics, highlight beach changes over time and their correlations with nesting success, and provide comparisons for nesting density models across large geographic areas.

Comparisons between the LiDAR dataset and other digital elevation models (DEMs) confirmed that fine spatial scale data sources provide more similar habitat information than those with coarser spatial scales. Although these studies focused solely on sea turtles, the underlying principles are applicable for many other wildlife species whose range and behavior may be influenced by topographic features.

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And for my family, this is for all of us.

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Chapter 1: Introduction

Animals move in space and time. For biologists studying wildlife species, much of the work and nearly all of the charm would be lost if animals, like plants, remained sedentary. However, as most creatures are mobile, and oftentimes hard to detect, a number of research techniques have been developed to try to overcome these obstacles.

One of the most common methods of determining number of individuals is to simply count them. Conducting a census of a population is rarely possible, except for singular cases such as breeding bird colonies (Reid & Huin, 2008) and larger, easier-to-detect species – especially those found in areas of sparse vegetation (e.g. hippos Karstad & Hudson, 1984). For most other species, a survey of populations remains a better choice to attempt to account for what is there. Survey methods range from transects (e.g. birds (Cimprich, 2009)) to capture-recapture (e.g. mice (Elmiger et al., 2010)) to using cameras or track plates (e.g. Foresman & Pearson, 1998).

Although of definite value, simply knowing, or hoping to know, the number of individuals tells only part of the story of a species' natural history. A further understanding of the interactions between a species and its habitat remains crucial to developing management plans. Early biologists, such as Joseph Grinnell, often recorded plant species and general geomorphological characteristics near their study sites in their field notebooks. Thousands of studies attempting to quantify habitat characteristics of a particular species exist (e.g. Varma, 2008; Weller, 2000; Zejda & Homolka, 1980), and

yet expanding the results of one study area to a larger range are risky and often advised against (Stromberg et al., 2009).

Therefore, for many species, habitat studies have been conducted in a piecemeal approach: sites were chosen based on a number of factors, including ease of access, and portions of a population's range that were more remote or difficult for data collection in may have been less studied (Rushton et al., 2004). Fieldwork is costly and time-consuming, and to expect a researcher to map large habitat areas in detail can be unwise.

The development of remote sensing techniques has filled a gap in biological research that resulted from spatial, logistical, and temporal constraints. Large areas can be characterized by physical features in a fraction of the time it would take to conduct ground work ((e.g. Liu et al. (2001) were able to analyze a study area of 200,000 ha using Landsat MSS and TM images) and more remote and/or dangerous areas can be studied from safer locales. Turner et al. (2003) suggested there are two main biology/ecology research arenas involving remote sensing data: direct remote sensing, such as using images to count trees or species groups; and indirect remote sensing of environmental proxies, such as mapping habitat.

Despite the incorporation of direct and indirect remote sensing analyses in ecological studies, the use of remote sensing is not yet widely adopted. Turner et al. (2003) highlighted two main roadblocks to the integration of remote sensing analyses to biologists and ecologists. The first roadblock, technology (which includes availability, scale, and cost of data, and training and practice with software), was presented by the authors as less of an issue as currently believed by many researchers. The ever-increasing

availability of data online, often free or of low-cost, and the increase of tools to analyze such data, have helped to assuage those technological concerns.

The second roadblock presented was that of culture. Turner et al. (2003) suggested that many biologists and ecologists believe that the scales used by field researchers do not match those provided by remote sensing images. This preconception, though largely false, has been an obstacle to the inclusion of remote sensing analyses to their studies. The potential of remote sensing is often disregarded as being of little to no use. The authors presented the challenge to such non-believers to shed their previous notions and become involved with collaborations between remote sensing researchers and biologists and ecologists (Turner et al., 2003).

Nine years later, this call to arms has been cited by more than 150 studies, and papers using remote sensing analyses to analyze wildlife habitat number in the hundreds, based on a search in Web of Science. However, as Turner et al. (2003) theorized, certain remote sensing data types, such as Light Detection and Ranging (LiDAR), hyperspectral, and radar, are still underrepresented in habitat analyses, due in part to their being "beyond the capabilities of most researchers" (Turner et al., 2003). Indeed, most studies that incorporate remote sensing analyses use images in the coarser spatial range, such as Landsat or MODIS (e.g. Hatten et al., 2010; Richardson et al., 2005), or secondary data products, such as land cover maps (e.g. Ficetola et al., 2010).

Chapter 2: Literature Review

One of the most common uses of remote sensing analyses for wildlife studies is the creation of habitat models. The goal of this type of modeling is to predict distribution of a species using both its presence or abundance in an area and the general characteristics of the area itself (Barry & Elith, 2006). In general, habitat modeling combines presence data (survey and/or historical data (e.g. Mueller et al., 2008; Anderson & Raza, 2010), with remotely sensed data layers to determine the suitability of an area for a particular species within the study area. The remote sensing data typically falls into one of two uses; either the images are classified into land cover categories (e.g. (Kaartinen et al., 2010) or image-based measurements are taken directly from the images without classification (e.g. Bellis et al., 2008). Both methods of utilizing remote sensing data are still commonly used by ecologists with the end goal of a habitat model that combines where the species was/is found and the variables that might help predict where the species is likely to be (Rushton et al., 2004).

There are three main types of statistical habitat models: envelope approaches which define the core area of a preferred habitat using a multidimensional profile; distance-based measures which incorporate the environmental distance between a site and the nearest presence record; and regression models which use a best-fit-curve through a set of points (Barry & Elith, 2006). Errors can be introduced at all levels of the modeling process, from the initial inputs of presence information to the model validation and use,

and have been addressed by many researchers (e.g. Barry & Elith, 2006; Guisan & Zimmermann, 2000).

A source of error which is often ignored is one that is inherent to the remote sensing images. Digital Elevation Models (DEMs), which are digital representations of topography, are frequently used to characterize physical characteristics of the landscape, such as slope, aspect, and elevation. DEMs are usually considered the "most accurate maps available" for habitat modeling (Guisan & Zimmermann, 2000) and are used as a base for many derived variables, but a DEM is often derived from another data source (e.g. topographic quadrangles, aerial photographs) and the spatial resolution of the DEM may be too coarse for the research goals of a study. Land cover maps, either in raster or vector format, are also frequently used as input to habitat models, but the locations of boundaries between classes are uncertain (Barry & Elith, 2006). In addition, the land cover maps may not have been originally derived for the study that uses them. No matter the data source, coarse spatial scale data may cause one pixel to cover the entire preferred range for a rare species or a species with a limited range.

2.1 Closing the Gap and New Integrations

Habitat models are an ideal method to determine suitability of an area for a species of interest. For those species with broad habitat requirements (i.e. habitat generalists) habitat models that use coarse-scale spatial data will likely suffice. Land cover maps may not need to be created specifically for the habitat model, and coarse-scale DEMs may only be needed to exclude areas with very steep slopes. However, for many species that have "pickier" habitat requirements, these coarser spatial scale datasets

that are commonly used will not be of much use. Nuanced details, such as extremes in slope, are lost in the pixelated surfaces.

Until the past few years, those nuances in topographical data were nearly impossible to capture in habitat models. With the recent development and availability of LiDAR data, a wide new range of habitat characterization studies are possible for those species where topography is a main limiting factor.

Therefore, the goal of this research is to illustrate that for those species where the surface relief and associated features are of utmost importance, the previous methods of obtaining habitat characteristics are not wholly appropriate. In addition, the research will highlight that LiDAR data can provide new topographical information in greater detail than other remote sensing- and fieldwork-derived data sources.

2.2 Target Species

In order to better illustrate this new approach in topography-driven wildlife habitat research, three studies were conducted to emphasize the ability to use LiDAR for research with the common goal of furthering the understanding of species. Sea turtle species that nest on the East Coast of the United States were used as the species of interest, although such an approach could be adapted to apply to any species for which topographic data will be of use.

Due to their elusive nature, sea turtles provide their own challenges to researchers. After hatching and becoming sea-bound, usually only the gravid females will return to land to nest, and then rarely in consecutive years (Vanbuskirk & Crowder, 1994). Studying the ocean behaviors of sea turtles remains difficult, and so most of the research

effort remains concentrated on the nesting beaches. Studies have historically been restricted to a single beach or closely neighboring beaches (e.g. Fowler, 1979; Hays & Speakman, 1993; Kamel & Mrosovsky, 2005)) with few attempts to make generalizations across a turtle species' range. Although such studies have value, the race to uncover as much information about sea turtles remains critical to their survival.

As a result of climate change and sea level rise, the low-lying beaches used by sea turtles for nesting are at risk of inundation, which may cause the extinction of entire populations (Fish et al., 2005; Fuentes et al., 2010). In addition, warming temperatures may skew the sex ratios, as a sea turtle's gender is determined by the temperature of the sand surrounding its egg; warmer temperatures result in the development of females (Morreale et al., 1982; Yntema & Mrosovsky, 1980). The need for increased research efforts to highlight preferred nesting area variables is of the utmost importance before current nesting areas are forever lost or the sex ratio forever altered.

There are currently seven recognized sea turtle species, six of which are either threatened or endangered (the sole remaining species, the flatback turtle (*Natator depressus*) does not have sufficient data to enable its listing (IUCN, 2010)). Threats to sea turtles include egg harvesting and habitat destruction (IUCN, 2010). Five of the seven sea turtle species nest in the United States (loggerhead (*Caretta caretta*), green (*Chelonia mydas*), leatherback (*Dermochelys coriacea*), olive ridley (*Lepidochelys olivacea*), and Kemp's ridley (*Lepidochelys kempii*)).

2.3 Sea Turtle Habitat Requirements

The beaches and nesting sites within beaches used by the seven different species vary, and few commonalities appear to exist. *Chelonia mydas*, for example, appear to prefer nesting near or within vegetation, as roots provide structure in nest building (Brown & Macdonald, 1995; Bustard, 1972; Bustard & Greenham, 1968; Chen et al., 2007). *Dermochelys coriacea*, however, which occasionally nest on the same beaches as *Chelonia mydas*, appear to prefer to nest in the open sand (Whitmore & Dutton, 1985). *Caretta caretta* also appear to prefer non-vegetated areas (Hays & Speakman, 1993) and the slope of the beach may help determine placement of nests (Provancha & Ehrhart, 1987; Wood & Bjorndal, 2000). The preferences of hawksbill turtles vary with individual females (Kamel & Mrosovsky, 2006). Other species, such as the Kemp's ridley and the flatback, have had limited research on nesting preferences.

The physical qualities of sand grains on the nesting beaches have been extensively quantified. An Ascension Island study showed no correlation with nest success and organic, water, or calcium carbonate content, pH, color, or grain size distribution (Stancyk & Ross, 1978). The sand grains of thirty-four nesting beaches from around the world were examined only to find that they had a wide range of characteristics (Mortimer, 1990).

Slope and the change of slope of nesting beaches as determining factors in sea turtle nesting area selection have been briefly studied. Beaches with a higher slope have higher nest densities than beaches with lower slopes for *Caretta caretta* (Provancha & Ehrhart, 1987). The beaches with the highest slopes, and thus the highest nesting

densities, have more gradual drop-offs offshore. The beaches with lower slopes and lower nesting densities tend to have near shore drop-offs bordered by shoals to the one side. Slope also appeared to be inversely correlated with beach width, and that offshore approach may be related to beach slope. As a result of these findings, the researchers suggest that offshore characteristics may influence a sea turtle's choice to nest on a nesting beach.

It has been hypothesized that slope and offshore configuration of the beach were possibly more important than sand grain properties, although the values have not been quantified (Mortimer, 1982). However, it is important to note that physical requirements of the different species and even individuals within the same species may determine beach selection. Because *Dermochelys coriacea* are much larger than *Chelonia mydas*, female *Dermochelys coriacea* may prefer to nest closer to shore than female *Chelonia mydas* simply due to energy constraints (Whitmore & Dutton, 1985).

The paltry number of studies to date focusing on the beach slope and offshore approach highlights the necessity to further investigate these parameters. In addition, because the morphology of the neighboring sea floor to the nesting beaches can affect the beach characteristics, such as sand grain size and beach slope, a greater understanding of these functions may help shed light on the inconclusive sand grain studies. Beach slope may also affect the amount and type of vegetation the beach is able to sustain, as well as affecting how near to shore the vegetation can grow. Thus, a method to characterize beaches based on beach slope and offshore approach, as well as linking these two

elements and noting how beaches change over years, seems to be an important missing piece in the literature.

The comparison of beach characteristics across geographical regions and species has yet to be explored in the literature, as most studies are focused on one or two species within a relatively narrow geographic range (usually a single beach). Single beach studies, though of great use in illustrating similarities and differences among populations, cannot always paint a picture of the species as a whole.

One of the goals of this research is to be able to quantify such characteristics as slope and offshore approach for beaches used by different species, which has yet to be presented in the literature. Each nesting beach will be treated as an entire unit and variability will compared between and within beaches. This technique differs from the more traditional approach of investigating the biophysical conditions in the vicinity of each nest. Although the immediate surroundings of a nest may explain why a specific turtle chose to nest in that area, it does not explain how beaches used by different species vary, or why neighboring beaches are used in varying degrees by the same species. Therefore, the factor of scale dictates which research focus is most applicable to the question at hand; namely, to compare beaches as a whole, entire beaches must be considered instead of individual nests.

Chapter 3: Problem Statement, Hypotheses, and Methods

The overarching goal of this dissertation is to determine how beach topography and bathymetry can be characterized to illustrate sea turtle nesting area preference. This main research question cannot be fully answered using traditional point sampling techniques, as a continuous data surface derived from high spatial resolution remote sensing data will more efficiently and thoroughly capture the structure of the land and seafloor surface.

Hypothesis 1: Morphological features such as offshore approach, beach slope, and slope change are related to sea turtle nesting preference by species. In addition, each species will have a range and degree of acceptability for different morphological features which can be quantified.

Hypothesis 2: Sea turtle nesting beaches change physically over a period of time, and these changes can reflect fluctuations in sea turtle nest success. Some morphological features are more prone to change than others.

Hypothesis 3: The results of hypotheses 1 and 2 integrate with current issues of data and scaling for sea turtle research, and the inclusion of new remote sensing data improve the predictive quality of habitat models. This hypothesis will be addressed by investigating if sea turtle nesting habitat predictions change with the addition of other remote sensing data sources.

3.1 Study Area

Within the United States, several states contain sea turtle nesting areas: Texas, Louisiana, Alabama, Florida, Georgia, and North and South Carolina. The Florida coast remains one of the largest *Caretta caretta* rookeries in the world, while also housing one of the largest *Chelonia mydas* nesting areas in the Atlantic and the only continuously used nesting area in the continental United States for *Dermochelys coriacea* (Meylan et al., 1995). In addition, the nesting areas of Florida are heavily monitored and nesting tallies are reported for each beach by the Florida Fish and Wildlife Conservation Commission (2008).

Therefore, the study area for this dissertation will focus on the Florida coast - specifically the southeastern coast of Florida (Figure 3.1), as there are beaches in this region that harbor up to three different turtle species and also contain some of the most heavily used beaches for *Caretta caretta* and *Chelonia mydas*. However, because the number of *Dermochelys coriacea* nesting in the United States is low, *Chelonia mydas* and *Caretta caretta* will be the main focus of this research.

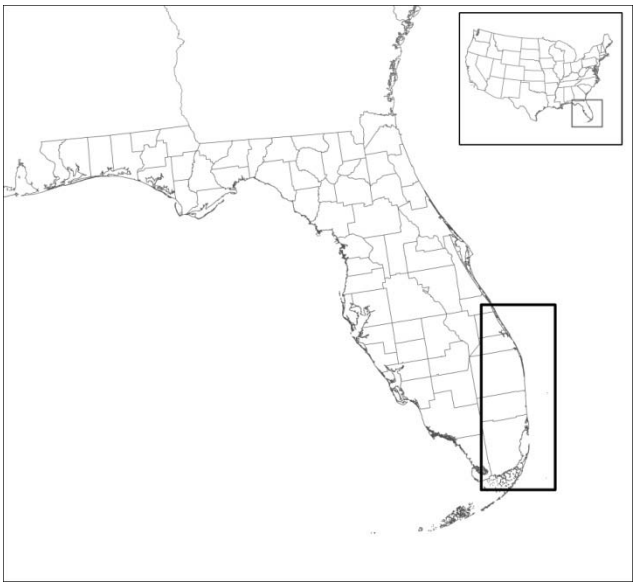

Figure 3.1 Study area within Florida to be the focus of the research questions.

3.2 Background of Suggested Sensor: LiDAR

LiDAR data has great promise for surveying beaches, due to its relatively low cost, continuous area that can be surveyed, and vertical and horizontal accuracy (Mason et al., 2000). Laser signals are sent as pulses from sensors onboard an aircraft to the ground below, typically in the ultraviolet (UV), visible, and near infrared (NIR) portions of the electromagnetic spectrum. The direction and time it takes for the laser pulse to return to the aircraft is measured and recorded, resulting in a series of points recording the height and orientation of objects on the ground. Most aircraft are also equipped with a Global Positioning System (GPS) to collect data geographic location data, as well as an inertial navigation data to correct for pitch, roll, and heading of the aircraft while in flight. Data obtained from LiDAR systems are obtained as a "cloud" of points, which can then be used to create accurate elevation maps, with vertical height accuracy of up to circa 15 cm and planimetric accuracy of up to circa 1 m on flat areas such as beaches that

contain little to no vegetation (Huising & Gomes Pereira, 1998). LiDAR can also be used to map seafloor topography near the shore if the water is clear (Estep et al., 1994).

Shoreline position can be difficult to delineate as a result of its dynamic and fickle nature. Traditional methods include marking the landward extent of the last high tide, or in cases where the high tide line cannot be easily established, physical features, such as vegetation line or dune line, may be used instead (Stockdon et al., 2002). However, such methods leave determination of the shoreline position to the discretion of the researcher, and errors can be present and of large magnitude (Boak & Turner, 2005).

As an alternative, LiDAR data can be used instead to automate the shoreline demarcation process. Cross-shore profiles for a study area can be created using the LiDAR images, allowing for the extraction of elevation data. Any pixels with excess noise as a result of waves and run-up are eliminated, and a linear regression model is run on the dataset with beach elevation as the independent variable, which then allows for the designation of water versus land (Stockdon et al., 2002).

In addition, LiDAR data can be combined with other auxiliary data to provide new research approaches. LiDAR data has been used in conjunction with multi-spectral images map coastal and estuarine habitat, and the incorporation of LiDAR data was demonstrated to enhance the accuracy of image classification, increasing the accuracy more than 10% in some habitat types (Chust et al., 2008). LiDAR has also been used to model habitat for plant species in coastal areas (Sellars & Jolls, 2007).

3.3 Methods for Each Hypothesis

3.3.1 Hypothesis 1: Characterizing Beaches and Predicting Nest Density

To address the first hypothesis (Morphological features such as offshore approach, beach slope, and slope change are related to sea turtle nesting beach use), the nesting beaches of southern Florida's coast will be categorized by species use and frequency of use, using nesting data from the Florida Fish and Wildlife Conservation Commission (2008). As there have yet to be any published studies comparing differences between nesting beaches used by a single or multiple species, all biophysical properties are of interest. Thus, comparisons of beach characteristics including slope, offshore approach, and size were completed.

Within the study area (Figure 1), all beaches that contain both bathymetric and topographic data and a consistent sampling effort (same number of days and same area surveyed per year) were included. Nesting data was averaged from 1998 to 2005 and LiDAR data will be from the 2005-2006 LiDAR collection window).

A list of all variables to be included in the analysis is included in Table 2. Data clouds for these beaches were procured from the National Oceanic and Atmospheric Administration (NOAA)'s LiDAR data portal, and the clouds were converted into Esri ArcGIS GRIDS for ease of processing. The cell size was calculated for the LiDAR data based on the original point spacing and the point at which the percentage of empty cells and the size of the cells are optimized.

For each cell, the average of all LiDAR data points were computed. Each pixel had geographic coordinates and an averaged elevation value, which allowed for shoreline

extraction. Noisy data points near or at the elevation of 0 m, which result from nearshore waves, indicated land from water. Onshore beach areas were assigned using the shoreline delineation as the seaward-most extent. The landward-most extent was assigned using the LiDAR intensity images which aided in identifying buildings and other artificial structures and the St Johns River Water Management District (2000) dataset, as used by Long et. al (2011). The areas classified as beaches, which were designated using 1:12,000 USGS CIR DOQQs, represent 1999 land use and land cover for Florida. Because of the date difference between this dataset and the LiDAR data, the beach areas were also compared to the LiDAR intensity images. For the majority of cases, the 1999 demarcations still applied.

Offshore beach areas used for this study were constructed using the designated shoreline as the nearshore extent and a 1 km area eastward from the shoreline as the offshore extent. The onshore and offshore beach bounding areas were used to extract data from the LiDAR rasterized elevation surfaces, as well as the derived slope, aspect, surface roughness, and slope comparison surfaces. Surface roughness, or rugosity, is commonly used in bathymetric studies. Rugosity is defined as the ratio of the surface area to the planar area (Jenness 2011). Terrain Positional Index (TPI) and the related Bathymetric Position Index (BPI) are derived from slope calculations, and they illustrate how a pixel in a surface is located relative to other pixels in the raster (Iampietro & Kvitek, 2002; Weiss, 2001). The variables that will be obtained for this study are summarized in Table 3.1.

Table 3.1. List of all variables to be investigated for hypothesis 1.

Variables to be Compared Between Beaches
Elevation, offshore and onshore
Slope, offshore and onshore
Beach length, width, area
Orientation, onshore
Aspect, onshore
Shoals, offshore
Surface roughness, offshore and onshore
Pixel slope comparison, offshore and onshore

The steps outlined above resulted in a number of variables with numeric values that will be used to characterize beaches used by certain sea turtle species. All the variables from Table 2, which include means, minimums, maximums, and standard deviations for the majority of the variables, were used to attempt to model nesting density (number of nests per km) for each species using stepwise linear regression. This statistical test identified which variable most contribute to nest density for each species.

The variables also identified extremes found in beaches that are used by sea turtle species. The minimum and maximum values for each variable were compared to nesting densities for each species to see if beaches that are used the most often have different values than beaches that are used less frequently. In addition, beaches with no documented use were compared to beaches with nesting activity. The same identification of extreme values was also used for comparison between species to see if species have overlapping acceptable values for nesting beaches.

3.3.2 Hypothesis 2: Change Over Time to Beaches and the Effects to Nest Success

To address the second hypothesis (Sea turtle nesting beaches change physically over a period of time, and these changes can reflect fluctuations in sea turtle nest success), a subset of the nesting beaches of southern Florida's coast from hypothesis 1 were used to evaluate changes from 1999-2004, and 2004-2006. To ensure consistency between dates, the St Johns River Water Management District (2004) areas identified as beaches were used as the boundaries for comparison, as the differences in timing of LiDAR collection will affect the onshore delineations from one dataset to the next. Only those beaches that are covered by the LiDAR data collections of the Airborne Topographic Mapper (ATM) II for 1999 and the Joint Airborne LiDAR Bathymetry Technical Center of Expertise (JALBTCX) using the Compact Hydrographic Airborne Rapid Total Survey (CHARTS) system for 2004 and 2006 were considered for inclusion in this study. As in hypothesis 1, the cell size for the LiDAR data was calculated based on the original point spacing and the point at which the percentage of empty cells and the size of the cells are optimized. The point spacing was different for hypothesis 2 (and hypothesis 3) than in hypothesis 1, based on the different LiDAR datasets and geographic areas used. For each hypothesis, the best spatial resolution for each study was selected.

The LiDAR data clouds were converted to rasters, and the following variables were measured: elevation, slope, surface roughness, pixel relative position, aspect, and volume. The change in variables from 1999 to 2004, and from 2004 to 2006, were reported (Table 3.2), and the change in volume was correlated with the change in the

other aforementioned variables to determine how the difference in the amount of sand and other beach materials present in a beach is related to change in other beach characteristics.

Table 3.2. List of all variables to be investigated for hypothesis 2

Variable	Measurements
Elevation	Minimum, maximum, mean, standard deviation
Slope	Minimum, maximum, mean, standard deviation
Aspect	Mean, standard deviation
TPI	Minimum, maximum, mean, standard deviation
Rugosity	Minimum, maximum, mean, standard deviation
Beach Length, Area	Total
Beach Volume	Total
Beach Orientation	Total

Nesting success, or the number of successful crawls (i.e. crawls that result in a nest), divided by the total number of crawls (Brock et al., 2009) was used to determine how changes in beach morphology affect sea turtle nesting behavior. The lower the nesting success, the less suitable the nesting area, and the change in nesting success can serve as a method to establish beach suitability from one year to another. The change in nesting success was compared to the changes in beach variables to identify which, if any, variable changes can be correlated to changes in nesting success.

3.3.3. Hypothesis 3: Modeling Habitat

The results from the previous research were used to evaluate if nest density models for *Caretta caretta* are applicable to other regions, or if each area necessitates its own model. In addition, the LiDAR data, with its high spatial resolution and optimal temporal resolution (collected shortly after the termination of nesting season), was compared to other freely available elevation datasets with coarser spatial resolution and

less optimal data collection dates, to illustrate how such differences influence modeling attempts.

The beaches and the 2006 LiDAR dataset used from hypotheses 1 and 2 were used to build a model for predicting nesting density for *Caretta caretta* from 2001 to 2005. Because bathymetric data is only available for the southern areas of Florida, only topographic details were incorporated. Similar to the methods in hypotheses 1 and 2, the St Johns River Water Management District (2004) was used to identify beach areas, and the variables listed in Table 3.3 were extracted from the rasterized LiDAR point cloud. Multivariate stepwise linear regressions were run to identify the best model to predict nesting density, using a balance between a high adjusted R^2 with the lowest number of variables and a low root-mean-square error (RMSE) and Akaike information criterion (AIC) value.

Table 3.3. List of all variables to be investigated for hypothesis 3

Variable	Measurements
Elevation	Minimum, maximum, mean, standard deviation
Slope	Minimum, maximum, mean, standard deviation
Aspect	Mean, standard deviation
TPI	Minimum, maximum, mean, standard deviation
Rugosity	Minimum, maximum, mean, standard deviation
Beach Length, Area	Total
Beach Orientation	Total

Fourteen beaches located north of the beaches used from hypotheses 1 and 2 were used to test the predictive power of the model in another region (Table 3.4). In addition to the CHARTS data, two DEMs were obtained from the USGS NED, representing 1/9 and 1/3 arcsecond spatial resolution (corresponding to roughly 3 m and 10 m). These NED

DEMs are created using a variety of datasets, and the temporal resolution spans over several years. Therefore, the effects of both differences in spatial and temporal resolution were compared to the LiDAR dataset.

Table 3.4. The 14 beaches, located in northern and central Florida along the Atlantic coast, used to test the model for *Caretta caretta* nesting density

Beach Name	**County**
Anastasia State Park	St. Johns
Flagler Beach SP	Flagler
Hanna Park	Duval
Mayport Naval Air Station	Duval
North Beach Club Drive	St. Johns
Old Ponte Vedra	St. Johns
Patrick Air Force Base	Brevard
Sebastian Inlet State Park	Brevard
South Beach Club Drive	St. Johns
South Cocoa Beach	Brevard
Vilano Beach	St. Johns
Wabasso Beach	Indian River
Wabasso Beach (South)	Indian River
Washington Oaks	Flagler

From each of the aforementioned datasets, the variables listed in Table 3.4 were extracted. In addition, the actual nesting density for each beach from 2001 to 2005 was calculated. The model resulting from the stepwise regression for the beaches from hypotheses 1 and 2 was then used to predict nesting density in the northern and central beaches, using the same variables, intercept, and coefficients identified in the model. Regressions between the actual and predicted nesting densities were run to determine the success of the predictive model for other areas. Separate models for each of the three elevation datasets were created for the fourteen beaches and then compared to the original model to highlight similarities and differences between the two region's turtles.

Finally, the research contained in this dissertation was designed based on the premise that finer spatial resolution and data collection dates close to the field season are optimal. The LiDAR dataset, which collection dates most closely match the end of nesting season, and with its fine spatial resolution, was compared to the NED DEMs using the values extracted for each of the beaches. It was assumed that the NED DEM with the spatial and temporal resolution most similar to the LiDAR dataset would result in the most comparable values.

The results from the three hypotheses outlined above shed insight into how beach topography and bathymetry can be characterized to illustrate sea turtle nesting area preference, if elevation-derived characteristics can be used to model nesting density and if such models can be used for other regions, how nesting areas change over time and if such changes affect nesting success, and finally, how the use of elevation datasets with different spatial and temporal resolutions can affect one's results. The subsequent chapters will answer each of these questions in depth.

Chapter 4: Using LiDAR to Quantify Topographic and Bathymetric Details for Sea Turtle Nesting Beaches in Florida

4.1. Introduction

Many coastal species are at risk due to habitat loss from beach construction and sea level rise. Sea turtles are particularly vulnerable, as all nesting efforts occur on low-lying beaches. Past research efforts, though intensive, have failed to determine exact requirements by different marine turtle species for nesting beaches. In addition, the characteristics of beaches and nesting sites within beaches used in by the seven different species vary globally, and few commonalities appear to exist. *Chelonia mydas* prefer nesting near or within vegetation (Brown & Macdonald, 1995; Bustard, 1972; Bustard & Greenham, 1968; Chen et al., 2007), while *Dermochelys coriacea*, prefer to nest in the open sand (Whitmore & Dutton, 1985). There is limited research on nesting preferences for other species.

Several biophysical elements that may influence nesting preference have been studied in depth *in situ*, including sand characteristics, moisture, salinity, beach width and length, amount of vegetation, and temperature (e.g. Bustard & Greenham, 1968; Mortimer, 1990; Stancyk & Ross, 1978). Morphological characteristics of beaches, such as slope and the related offshore approach, have been the addressed in studies, but not to

the same extent as the above characteristics. For example, Horrocks and Scott (1991) found that nest elevation above sea level was positively related with hatching success for hawksbill turtles, *Eretmochelys imbricate.* Their study also found that on beaches with less steep slopes, hawksbills nested further from the high tide line, which suggests that hawksbills prefer to nest at a certain mean elevation above sea level, and therefore the females will travel further inland in order to reach the optimum elevation value, even if it means traveling greater distances. In addition, the researchers hypothesized that because on-land travel is energy expensive for female hawksbills, females will prefer to nest on beaches with steeper slopes, as they have less distance to travel inland. The newly hatched young also will benefit from the steeper slope when traveling towards the ocean as they will not have to travel as far to reach the ocean.

Provancha and Ehrhart (1987) also reported that segments of beaches with higher slopes had higher nest densities than beaches with lower slopes for *Caretta caretta*. They attributed this preference to beaches with higher slope being classified as high-energy beaches, and beaches with lower slope classified as low-energy beaches. The beaches with the highest slopes, and thus the highest nesting densities, had more gradual drop-offs offshore. The beaches with lower slopes and lower nesting densities had nearshore drop-offs bordered by shoals to the one side. The researchers also found that slope and width of nesting beaches were inversely correlated, and that offshore approach may be related to beach slope. As a result of these findings, the researchers suggest that offshore characteristics may influence a sea turtle's choice to nest on a nesting beach.

In addition to offshore sea bed approach, obstacles within the water also affect a sea turtle's use of a beach for nesting. Bouchard et al. (1998) found that artificial pilings constructed from PVC pipe to stabilize sand and decrease the effects of erosion can significantly decrease nesting activity of *Caretta caretta* and *Chelonia mydas*. Other offshore elements may also help predict the use of a beach for nesting by sea turtles.

Based on these few studies, it appears that slope and offshore approach may be important factors in beach selection, the first step in nesting activity. Mortimer (1982) also hypothesized that slope and offshore configuration of the beach were possibly more important than sand grain properties, although the values were never quantified. However, it is important to note that physical requirements of the different species and even individuals within the same species may determine beach selection. Whitmore and Dutton (1985) suggested that because *Dermochelys coriacea* are generally much larger than *Chelonia mydas*, female *Dermochelys coriacea* may prefer to nest closer to shore than female *Chelonia mydas* due to energy constraints.

Better methods to extract topographic information from coastal areas are a current need in ecological studies. DEMs are commonly used, due to their relatively low (or no) cost when procured from governmental sources and their widespread geographic availability. However, the spatial and temporal resolution of DEMs is dependent upon the original data provider, and the spatial resolution in particular can be too coarse for small study areas (e.g. the Shuttle Radar Topography Mission (SRTM) DEM has a spatial resolution of 90 m globally, and 30 m for the United States).

LiDAR data have been used successfully when other commonly used DEMs are not deemed adequate due to their spatial or temporal resolution. Of particular interest to researchers in coastal areas is the ability to quickly highlight small elevational differences across the coastal landscape. Stockdon et al. (2009) utilized LiDAR data to identify dune crests in hurricane-prone areas, which can be used in creating vulnerability maps to aid in disaster planning. Dune erosion from grazing activities can also be quantified with LiDAR (De Stoppelaire et al., 2004), and low-lying areas prone to inundation from sea level rise are more easily identified with LiDAR than other data sources (Gesch, 2009).

Bathymetric features are also possible to visualize using LiDAR with a dual laser system, instead of the single laser used for topographic mapping (Quadros et al., 2008). Aircraft-based LiDAR sensors, in particular, are a more effective method of mapping offshore areas without the need of boat-mounted sonar or laser methods, which can damage shallow water ecosystems (Parson et al., 1997). Collin et al. (2008) used LiDAR to map the shallow water seabed to aid in habitat identification. Also pertaining to off-shore habitat mapping, Zawada and Brock (2009) illustrated that the topographic complexity of coral reefs can be quantified using LiDAR data.

Prior to the use of LiDAR, multibeam sounding data were primarily used to map the ocean floor, and many of the techniques later adopted for LiDAR were originally developed for multibeam data. Similar to LiDAR data, multibeam soundings can be converted to rasters and then treated as an elevational surface. Aside from the expected derived variables, such as mean elevation, slope, aspect, and orientation, two additional variables are commonly calculated to characterize features and highlight changes in

elevation across a landscape. TPI and the related BPI are derived from slope calculations and illustrate how a pixel in a surface is located relative to other pixels in the raster (Iampietro & Kvitek, 2002; Weiss, 2001). This relative location (e.g. higher or lower than a pixel's neighbors) can be calculated using a number of nearest neighbor algorithms, including the use of circles or rectangles (Lundblad et al., 2006).

Surface roughness, or rugosity, is also commonly used in bathymetric studies. Rugosity is defined as the ratio of the surface area to the planar area (Jenness, 2011). Areas with a rugosity value of 1 are flat, indicating no difference between the surface area to planar area ratio. Areas with rugosity values greater than 1 have some degree of roughness, with higher values indicating a greater degree of roughness. For example, a Himalayan peak will have a higher rugosity value than a cornfield in Iowa representing the same ground area. Rugosity calculated from LiDAR-derived surfaces corresponds well with in-situ measurements for finer spatial resolutions (Wedding et al., 2008).

Depth, slope, TPI/BPI and rugosity are useful in the creation of a benthic classification system of topographic features (Lundblad et al., 2006). On the ecological side, these variables have been used to identify and predict benthic biotopes (Buhl-Mortensen et al., 2009), to identify benthic habitats (Wilson et al., 2007), and create rockfish predictive models (Iampietro et al., 2008). TPI alone has been used to classify topographic features, such as valleys and canyons, (Weiss 2001), or combined with rugosity to classify seafloor habitats (Iampietro and Kvitek 2002).

Few studies have compared multiple sea turtle nesting beaches to one another; Mortimer (1990) remains one most often-cited. The lack of studies that compare multiple

beaches, topographically and bathymetrically, for multiple species represents a gap in the literature. This gap is largely a result of the time-intensive nature of gathering elevation data in the field, and the difficulty of collecting bathymetric data in general. The relatively recent availability of LiDAR data now enables researchers to conduct elevation-based studies that were previously logistically impossible.

The goals of this research are to investigate the following two questions using LiDAR data and annual turtle nest surveys: (1) Do beaches used by the same species show similar morphological characteristics, and to what degree do these characteristics overlap between species? (2) Can morphological characteristics be used to model sea turtle nesting density? Although the study area will be limited to southeastern Florida, the methods are assumed to be generalizable to other areas of interest.

4.2. Methods

Beaches were used as the basic spatial unit of analysis in this study, rather than the areas directly surrounding nests. Although the environment in the immediate vicinity of a nest provides insight into why a female chooses to nest at that particular site, and may reveal differences between individuals and within beaches, beach-wide comparisons can highlight similarities and differences across larger geographic areas. In addition, because beaches are used by different species to varying degrees, allowing comparisons at a beach level can potentially highlight a broader range of suitability values for and between species. Finally, data on turtle nesting density were only available at the beach level.

Nesting information was obtained from the Florida Fish and Wildlife Conservation Commission (FWC) (2008). The data contain the number of nests per beach per year by species, dates of nesting seasons, areas of beach surveyed, and the number of days per week spent surveying. Beaches were included in the current study if monitoring efforts were conducted between 1998 and 2005 with a relatively consistent sampling area and effort. For example, beaches were only included if the surveyed area of a beach varied less than 0.25 km between years and if the number of surveying days conducted per week remained constant between years. In addition, only those beaches with LiDAR coverage within the boundaries for the bathymetric and topographic mapping project by the United States Army Corps of Engineers were considered. On the east coast of Florida, a total of 21 beaches were ultimately included in this study (Table 4.1, Figure 4.1).

Table 4.1. List of the 21 beaches, and their associated counties and area, included in the study.

Beach Name	County	Area (km^2)
Boca Raton Beaches	Palm Beach	0.390
Deerfield/Hillsboro Beaches	Broward	0.248
Delray Beach	Palm Beach	0.338
Ft Lauderdale Beach	Broward	0.602
Golden Beach	Miami-Dade	0.109
Gulfstream	Palm Beach	0.237
Gulfstream Park	Palm Beach	0.004
Highland Beach	Palm Beach	0.016
Hobe Sound NWR	Martin	0.238
Hollywood/Hallandale Beach	Broward	0.583
John U. Lloyd State Park	Broward	0.267
Jupiter Island	Martin	0.027
Kreusler Park	Palm Beach	0.013
Lake Worth Municipal Beach	Palm Beach	0.017
Lantana	Palm Beach	0.007
Macarthur State Park	Palm Beach	0.003

Beach Name	County	Area (km^2)
Ocean Inlet Park	Palm Beach	0.010
Ocean Reef Park	Palm Beach	0.013
Pompano/Lauderdale-by-the-Sea	Broward	0.617
Singer Island	Palm Beach	0.076
Sloan's Curve	Palm Beach	0.050

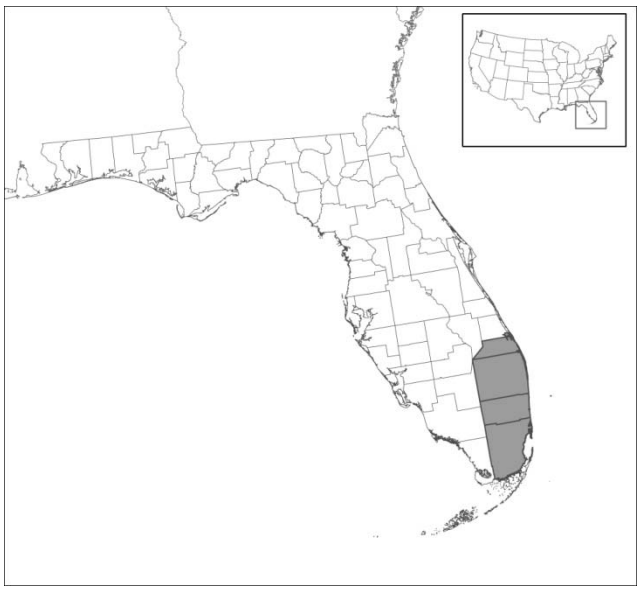

Figure 4.1. Counties in Florida with beaches included in the analysis

Each beach was divided into two areas, onshore (from the inland-most points still classified as beach to the shoreline) and offshore (from the shoreline to a specified point ocean-ward) for analysis. The onshore and offshore areas were used to extract values from the LiDAR-derived rasters, which were then compared across beaches and species. The steps for these processes are detailed below.

LiDAR data were procured from the NOAA Coastal Services Center's Digital Coast website in UTM Zone 17 projection with NAD83 horizontal and NAVD88 vertical datum, LAS 1.1 file format. The data originated from a 2006 topographic and

bathymetric mapping project from the United States Army Corps of Engineers and were collected by the JALBTCX using the CHARTS system. LiDAR data collection flights were flown from December 2005 to February 2006, which corresponded to roughly one to two months after the nesting season of 2005 completed. The LiDAR flights were typically conducted at low tide (Sylvester, 2011), and the timing of all LiDAR flights allowed for covering summer accretion before winter storm erosion. Vertical accuracy is 0.30 meters within two standard deviations, horizontal accuracy is 3.0 meters within two standard deviations, and the nominal ground spacing of LiDAR samples is 2.0 meters.

The LiDAR cloud data were converted to rasters with varying pixel sizes in order to determine the pixel size that resulted in the best balance between a low percentage of empty cells (i.e. cells with no LiDAR data points) and a minimal amount of data point averaging, which would result in a loss of detail included in the original data. Three sample areas with approximately 400 by 400 m dimensions were chosen from Delray, Golden, and Lantana beaches. For each sample area, LiDAR cloud data were converted to pixels with spatial resolutions varying between 2 and 10 m using the Boise Center Aerospace Laboratory (BCAL) LiDAR toolset, as described in Streutker and Glenn (2006), available as an Exelis Visual Information Solutions ENVI add-on (http://bcal.geology.isu.edulEnvitools.shtml). Points with an elevation five or more standard deviations from the median value for the dataset were considered outliers and not included in the raster datasets. The percentage of empty cells in each sample area was calculated for each pixel size (Figure 4.2). As expected, the percentage of empty cells decreased as the pixel size increased. By the 9 m spatial resolution, there were no empty

cells remaining. Based on these results, a pixel size of 5 m for all beaches was chosen for this study, as 5 m resolution minimized empty cells without overly smoothing the original data. The resulting elevation rasters were used to construct slope rasters, measured in degrees, and TPI/BPI, rugosity, and aspect raster datasets.

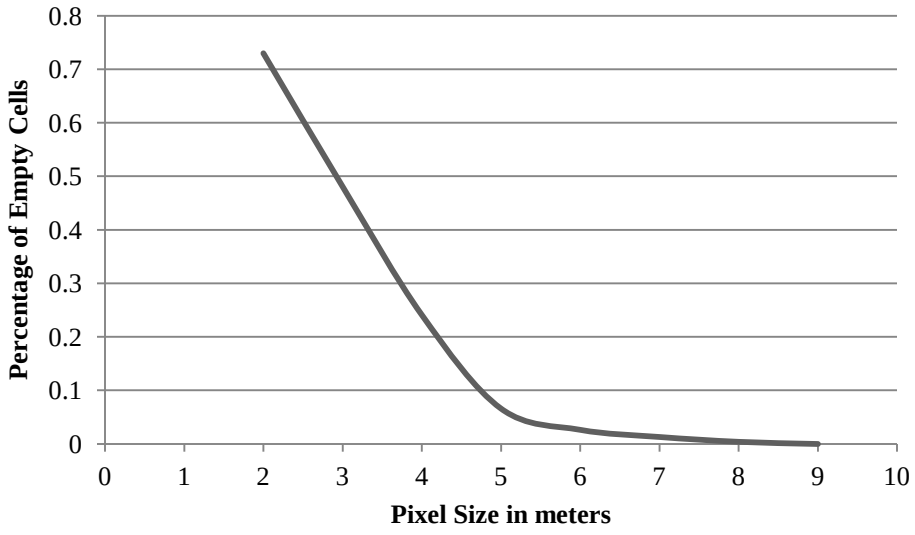

Figure 4.2. Percent of no-data cells versus pixel size of raster image generated from LiDAR data (example from Delray Beach, Palm Beach County.)

Although the length and location of the beaches was included in the data provided by the FWC, the defining boundaries of the beaches as provided by the FWC did not always match up with the LiDAR data from 2006. As a result, the St Johns River Water Management District (SJRWMD) (2004) dataset was used to delineate the coastal areas for consistency to subset the LiDAR data into beach areas, similar to the methods implemented by Long et. al (2011). This dataset originates from color and color infrared aerial photography taken from December 2003 to March 2004 and represents land use and land cover for Florida as polygons. Due to the differences in dates of data acquisition, the boundaries of beach areas from the SJRWMD were overlaid on the

intensity images from the LiDAR data for comparison. In the vast majority of cases, the areas designated as beaches in the SJRWMD dataset could be used to delineate the beaches, as the 2004 demarcations still applied. For those areas that did not match well, the LiDAR data were used to adjust the 2004 boundaries. The transition from sand (beach) to vegetated areas with buildings (non-beach) was relatively easy to identify using the LiDAR intensity surfaces. Piers and other beach structures were not included in the analysis and were removed from the polygons, as they skew the onshore and offshore heights and slope measurements.

Once the onshore delineations were established, the shoreline and the offshore boundaries were generated. As a result from waves breaking on the land, the LiDAR data contained gaps (or no data) at around 0 m elevation mean sea level (MSL). This area of no data, when digitized and overlaid onto Google Earth imagery (date 12/30/2005), corresponded well with the shoreline in the images. Thus, the first no-data pixels in a direction perpendicular to the beach area were designated as the shoreline.

In order to determine the offshore boundaries, the bathymetric dataset was subset to include the area from the shoreline to 1000 m offshore. This distance was chosen to best compare offshore depth and other variables between beaches, because beaches had different widths of offshore areas charted with LiDAR. Although many of the LiDAR datasets contained data far beyond 1000 m, some beaches did not, and using the entire bathymetric dataset would potentially skew the results, as the beaches with data for the furthest distance offshore would likely have the greatest depths.

Thus, for each beach, two polygons represented areas of interest: offshore and onshore (Figure 4.3). In addition, rasterized LiDAR intensity surfaces were generated for each beach with elevations for both offshore and onshore areas. These elevation surfaces were used to generate rasters representing slope and aspect for each pixel. TPI/BPI and rugosity raster surfaces were used to further represent surface characteristics. The TPI/BPI grids were created using the CorridorDesigner extension for Esri's ArcMap 9.3 (Majka et al., 2007) with the circle filter and a radius of four pixels to capture changes in the landscapes without overly averaging values (four pixels was chosen as it creates a neighborhood of 20 m from which to determine the TPI/BPI values, which allows for a compromise between small and large neighborhood averaging). Rugosity grids were produced with the DEM Surface Tools for ArcGIS 9.x (Jenness, 2011). The elevation, slope, aspect, TPI/BPI, and rugosity rasters were all clipped to only include the offshore and onshore areas of interest. Other variables, such as orientation, length, and width of the beach, were recorded. The presence of offshore shoals and their area were also noted, as the presence of shoals has been attributed to lower nesting densities in *Caretta caretta* (Provancha & Ehrhart, 1987). Because the compass direction orientation and aspect are cyclical variables, they were transformed to their non-cyclical forms for eastness using the sine function (Austin et al., 1990; Pierce et al., 2005; Piedallu and Gegout, 2008). All of the above measurements and were then used to extract a number of variables for each beach (Table 4.2).

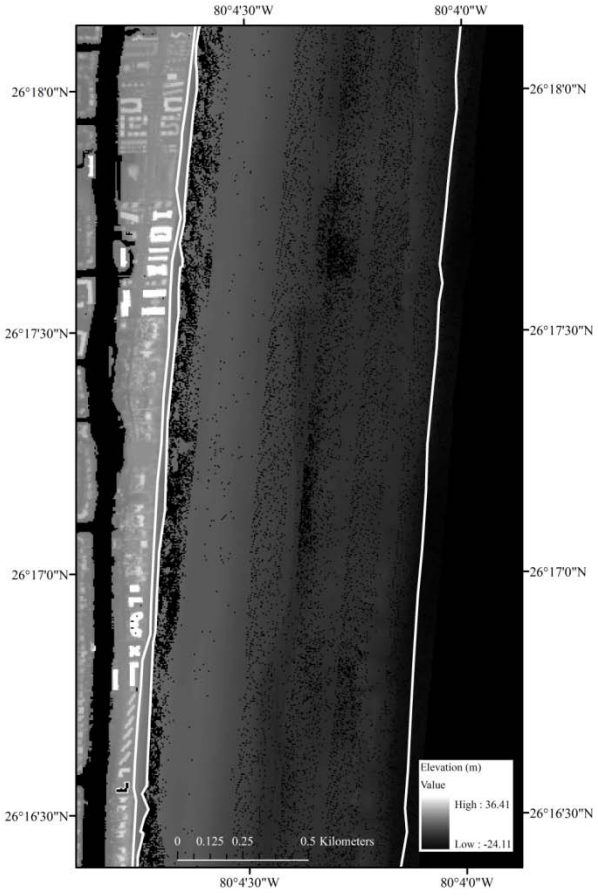

Figure 4.3. Example of LiDAR elevation raster with a portion of Deerfield/Hillsboro Beaches represented. The onshore and offshore polygons, shown in white, were used to extract variables from the elevation and elevation-derived raster datasets.

Table 4.2. Variables and abbreviated names used in the analysis

Variable	Measurements
Onshore Elevation	Minimum, maximum, mean, standard deviation
Offshore Elevation	Minimum, maximum, mean, standard deviation
Onshore Slope	Minimum, maximum, mean, standard deviation
Offshore Slope	Minimum, maximum, mean, standard deviation
Aspect Onshore	Mean, standard deviation
Aspect Offshore	Mean, standard deviation
TPI Onshore	Minimum, maximum, mean, standard deviation
BPI Offshore	Minimum, maximum, mean, standard deviation
Rugosity Onshore	Minimum, maximum, mean, standard deviation
Rugosity Offshore	Minimum, maximum, mean, standard deviation
Offshore Shoals	Area
Beach Length	Total
Beach Width	Minimum, maximum, mean
Beach Orientation	Total

Similarities between beaches with a similar number of nests per km were evaluated to determine whether beaches with a higher degree of use were characterized by different ranges of morphological variables than beaches with less use. Jenks natural break optimization divisions were applied to the turtle nesting density dataset to assign each beach into one of three classes for each species: high, medium, and low nesting density. This method divides the data into a predetermined number of classes by minimizing the average deviations from the class mean (Jenks, 1967). These ranks were used to compare beaches of similar nesting use within and between species based on morphological variables.

The variables for each rank were combined. The minimum, maximum, and average of the mean values were calculated for each variable for each rank of the species. Beaches with the highest degree of use for each species were expected to have the

narrowest ranges for the most important variables that determine beach use, converging on an "ideal" range for the nesting preferences of that species. Conversely, beaches with less use by a given species were expected to have wider ranges for the important variables, representing the degree to which a beach would be considered suitable for nesting but not able to support larger numbers of nests.

To determine if the beaches with the highest use for each of the species (rank = "high") were characterized by morphologic measures that were statistically different from one another, ANOVA tests were run for offshore and onshore elevation, slope, TPI/BPI, rugosity, and aspect, and beach length, width, and orientation using the mean of the means and the square root of the average of the standard deviations for each variable.

To determine which variables were most strongly associated with turtle nesting density for each species, stepwise multiple linear regression was conducted using SAS Institute Inc's JMP Pro 9.0. The average number of nests per kilometer from 1998-2005 was used as the response variable. All variables that could potentially be related to nesting activity were originally considered for inclusion in the modeling attempts as the predictor variables. Slope has already been shown to correlate with nesting density (Provancha and Ehrhart 1987), and elevation with nest location preferences (Horrocks and Scott 1991). Offshore shoals may also be related to nest density (Provancha and Ehrhart 1987), and beach orientation, aspect, and length and width measurements provide additional information that may affect beach morphology. While BPI/TPI and rugosity have not been previously used for sea turtle habitat modeling, they have been incorporated into other marine habitat models, such as Iampietro et al. (2008). The

miminum, maximum, mean, and standard deviation of slope and elevation, both for onshore and offshore areas, were included, as were offshore shoal and onshore aspect, width, and length measurements.

For rugosity and BPI/TPI, maximum, mean, and standard deviation of values were included; however, offshore mean BPI and offshore and onshore minimum rugosity had values too similar across all beaches to be included in the model. In addition, minimum BPI/TPI measurements were removed from consideration as sea turtles coming ashore to nest may be less affected by the lowest areas than the surroundings, and more affected by the highest peaks and overall landscape surface characteristics. Stepwise multiple regressions were run to determine the best model for each species, with a balance sought between low root-mean-square error (RMSE) and Akaike information criterion (AIC) values, and high adjusted R^2 with a minimum number of variables.

4.3. Results

4.3.1 Beach-wide Comparisons within and between Species

4.3.1.1 Within Species

The Jenks divisions divided the beaches into rankings for average number of nests per km per species (Table 4.3), and the assigned rank for each beach, and the ranges observed for each variable, are shown in Table 4.4.

Table 4.3. Jenks divisions for average number of nests per km for each species. The values represent the upper limit for each category. Sample size n = 21.

	Rank Low	Rank Med	Rank High
C. caretta	76.63	196.05	372.84
C. mydas	9	21.32	62.33
D. coriacea	1.11	3.36	7.19

Table 4.4. Beaches and their assigned rank for each species. Minimum and maximum values are reported for elevation, slope, TPI/BPI, rugosity, and beach width.

				Onshore variables								
Beach	*C. caretta* use	*C. mydas* use	*D. coriacea* use	Onshore Elevation	Onshore Slope	Onshore TPI	Onshore Rugosity	Onshore Aspect	Beach Length (km)	Beach Width (m)	Sine Beach Orientation	Sine Beach Aspect
Boca Raton Beaches	Med	Med	Med	-1.29 – 6.34	0.04 – 34.00	-2.16 – 2.25	1.00 – 1.11	102.14	7.60	26.19 – 83.29	0.16	0.98
Deerfield/Hillsboro Beaches	Med	Med	Med	-1.70 – 6.38	0.02 – 24.55	-0.53 – 0.74	1.00 – 1.02	98.41	6.90	15.64 – 80.46	0.13	0.99
Delray Beach	Low	Low	Med	-1.47 – 5.54	0.01 – 14.70	-0.79 – 1.07	1.00 – 1.04	111.97	4.80	48.05 – 99.29	0.17	0.93
Ft Lauderdale Beach	Low	Low	Low	-1.58 – 6.35	0.14 – 25.32	-3.90 – 3.09	1.00 – 1.14	111.67	10.50	26.76 – 142.40	0.14	0.93
Golden Beach	Low	Low	Low	-0.66 – 6.39	0.01 – 28.77	-1.36 – 2.68	1.00 – 1.20	160.96	1.97	44.54 – 71.62	0.07	0.33
Gulfstream	Low	Med	Med	-2.06 – 5.20	0.00 – 22.41	-1.17 – 3.5	1.00 – 1.19	101.47	2.71	15.83 – 56.60	0.12	0.98
Gulfstream Park	Med	Low	None	-1.04 – 3.17	1.95 – 32.38	-1.12 – 0.23	1.00 – 1.01	97.93	0.13	33.47 – 38.00	0.15	0.99
Highland Beach	Med	Med	Med	-1.45 – 5.77	0.00 – 52.24	-6.42 – 2.38	1.00 – 1.08	98.12	4.62	20.34 – 74.68	0.08	0.99
Hobe Sound NWR	High	Med	High	-1.94 – 5.95	0.02 – 32.54	-1.13 – 1.91	1.00 – 1.05	72.51	5.30	28.51 – 55.99	-0.35	0.95
Hollywood/Hallandale Beach	Low	Low	Low	-0.75 – 7.12	0.01 – 15.71	-3.91 – 3.97	1.00 – 1.38	114.74	9.30	30.68 – 86.94	0.11	0.91
John U. Lloyd Beach State Park	Low	Low	Low	-0.76 – 4.92	0.02 – 16.80	-1.47 – 2.40	1.00 – 1.06	147.58	3.70	40.45 – 111.6	0.13	0.54
Jupiter Island	High	Med	High	-2.54 – 9.63	0.00 – 39.25	-1.74 – 5.99	1.00 – 1.32	92.88	13.61	24.12 – 97.82	-0.32	1.00
Kreusler Park	Low	Low	High	-1.47 – 2.00	1.43 – 11.77	-0.61 – 0.18	1.00 – 1.02	87.73	0.50	17.50 – 36.81	-0.03	1.00
Lake Worth Municipal Beach	Low	None	Low	-1.05 – 10.20	1.87 – 45.12	-2.79 – 7.08	1.00 – 1.43	94.77	0.40	42.80 – 46.23	-0.01	1.00
Lantana	Low	Low	Med	-0.10 – 3.80	0.95 – 26.64	-1.38 – 1.46	1.00 – 1.07	91.79	0.20	31.70 – 41.73	0.08	1.00
Macarthur State Park	High	High	High	-2.16 – 3.56	0.06 – 22.34	-1.53 – 1.09	1.00 – 1.06	84.51	2.54	22.68 – 41.92	-0.20	1.00
Ocean Inlet Park	Low	Low	Low	-1.69 – 3.84	0.71 – 15.92	-0.72 – 1.30	1.00 – 1.02	135.55	0.19	54.38 – 62.09	0.25	0.70
Ocean Reef Park	Med	Low	High	-0.57 – 5.22	0.07 – 30.98	-0.73 – 1.99	1.00 – 1.04	105.62	0.20	31.91 – 77.52	0.35	0.96
Pompano/Lauderdale-by-the-Sea	Med	Low	Low	-1.76 – 6.37	0.00 – 26.40	-4.51 – 3.50	1.00 – 1.14	117.91	7.60	53.40 – 136.30	0.19	0.88
Singer Island	High	High	High	-4.24 – 12.50	0.00 – 33.07	-0.92 – 0.73	1.00 – 1.25	115.25	3.20	17.87 – 121.50	-0.06	0.90
Sloan's Curve	High	High	High	-1.58 – 3.65	0.02 – 28.23	-2.05 – 0.67	1.00 – 1.04	108.73	1.33	33.57 – 53.23	0.01	0.95

Table 4.4. continued

Beach	*C. caretta* use	*C. mydas* use	*D. coriacea* use	Offshore variables					
				Offshore Elevation	Offshore Slope	Offshore BPI	Offshore Rugosity	Sine Offshore Aspect	Shoals Area (km2)
Boca Raton Beaches	Med	Med	Med	-22.18 – -0.11	0.00 – 16.10	-1.27 – 1.04	1.00 – 1.05	0.90	0.47
Deerfield/Hillsboro Beaches	Med	Med	Med	-23.75 – -0.66	0.00 – 33.37	-1.30 – 0.97	1.00 – 1.06	0.79	0
Delray Beach	Low	Low	Med	-26.63 – -0.24	0.00 – 18.10	-1.94 – 1.53	1.00 – 1.09	0.85	0.82
Ft Lauderdale Beach	Low	Low	Low	-12.16 – 0.05	0.00 – 16.73	-1.41 – 2.18	1.00 – 1.11	0.30	0
Golden Beach	Low	Low	Low	-10.95 – 0.17	0.00 – 7.70	-1.60 – 2.09	1.00 – 1.13	0.36	0
Gulfstream	Low	Med	Med	-18.05 – -0.10	0.00 – 6.38	-0.75 – 0.60	1.00 – 1.01	0.90	0
Gulfstream Park	Med	Low	None	-15.69 – -0.71	0.00 – 7.31	-0.77 – 0.56	1.00 – 1.01	0.87	0
Highland Beach	Med	Med	Med	-21.92 – 0.12	0.00 – 5.92	-1.09 – 0.81	1.00 – 1.03	0.94	0
Hobe Sound NWR	High	Med	High	-14.2 – -0.33	0.00 – 16.40	-1.74 – 1.94	1.00 – 1.08	0.66	0.80
Hollywood/Hallandale Beach	Low	Low	Low	-12.85 – 0.17	0.00 – 13.40	-4.04 – 6.84	1.00 – 1.90	0.48	0
John U. Lloyd Beach State Park	Low	Low	Low	-10.21 – -0.32	0.00 – 11.70	-3.57 – 3.03	1.00 – 1.44	0.47	0
Jupiter Island	High	Med	High	-12.26 – 1.80	0.00 – 12.10	-2.24 – 1.74	1.00 – 1.18	0.90	0
Kreusler Park	Low	Low	High	-14.53 – -0.88	0.00 – 5.40	-0.48 – 0.40	1.00 – 1.01	0.98	0
Lake Worth Municipal Beach	Low	None	Low	-17.72 – -1.30	0.00 – 8.62	-1.19 – 0.69	1.00 – 1.03	0.98	0
Lantana	Low	Low	Med	-13.95 – -0.97	0.01 – 4.61	-0.48 – 0.44	1.00 – 1.01	0.93	0
Macarthur State Park	High	High	High	-13.45 – -0.16	0.00 – 11.3	-1.29 – 1.18	1.00 – 1.05	0.94	0
Ocean Inlet Park	Low	Low	Low	-16.29 – -0.40	0.02 – 7.61	-0.92 – 0.53	1.00 – 1.01	0.96	0
Ocean Reef Park	Med	Low	High	-18.89 – 0.27	0.00 – 11.70	-1.07 – 1.34	1.00 – 1.07	0.80	0
Pompano/Lauderdale-by-the-Sea	Med	Low	Low	-18.64 – 0.12	0.00 – 26.80	-2.16 – 3.12	1.00 – 1.23	0.53	0.28
Singer Island	High	High	High	-20.94 – -0.98	0.00 – 14.10	-0.91 – 1.02	1.00 – 1.11	0.95	0
Sloan's Curve	High	High	High	-14.43 – -0.76	0.00 – 9.52	-0.84 – 0.75	1.00 – 1.03	0.97	0

Offshore and onshore elevation, slope, TPI/BPI, and rugosity were compared across ranks for each species. Some of the variables demonstrated a clear gradient for each species, with low rank beaches having the greatest variability and the highest ranking beaches having less, such as BPI offshore (Figure 4.4). (For *Caretta caretta*, offshore and onshore BPI and offshore rugosity showed such gradients; for *Chelonia mydas*, offshore and onshore rugosity and offshore BPI did; none of the variables tested for *Dermochelys coriacea* demonstrated such a pattern). The remaining variables showed no distinct trends, such as onshore elevation (Figure 4.5).

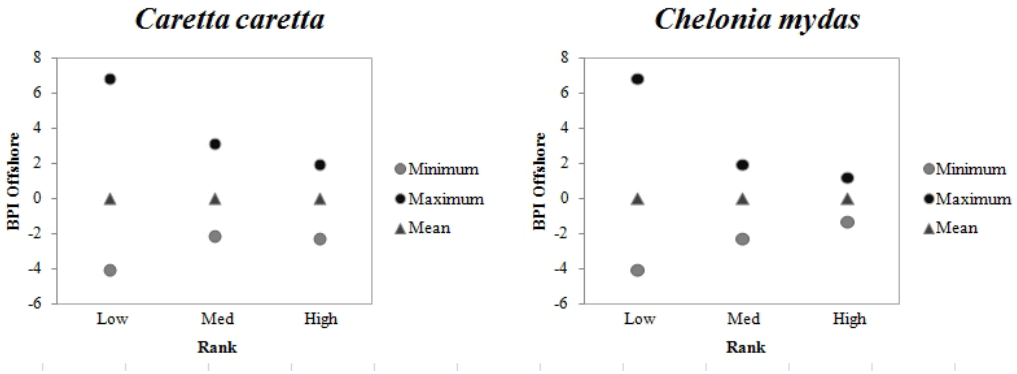

Figure 4.4. BPI offshore measurements (minimum, maximum, and mean BPI offshore) for *Caretta caretta* and *Chelonia mydas*.

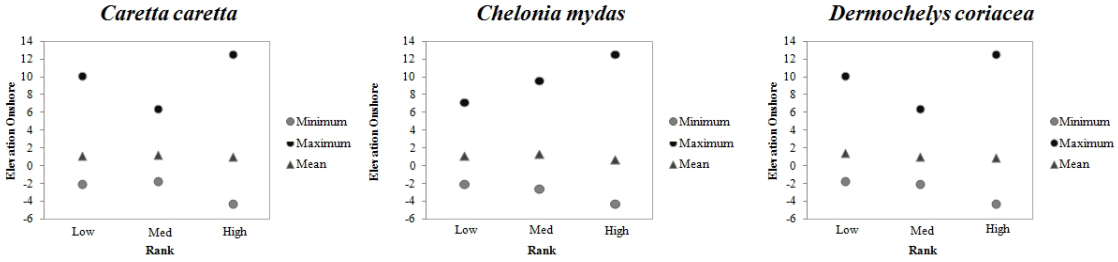

Figure 4.5. Elevation onshore measurements (minimum, maximum, and mean elevation onshore) for each of the three species.

4.3.1.2 Between Species

Based on the ANOVA tests, none of the variables were statistically different between species at the $p<0.10$ significance level. This indicates that the beaches with the

highest use for the three species contained similar means for each of the variables tested. This result is not surprising, as there is overlap between many of the highest rank beaches.

The range of values present on nesting beaches for each species were compared for elevation, slope, TPI/BPI, rugosity, length, width, orientation, and aspect to establish minimum and maximum suitability values. Because most of the nesting beaches were used by all three species, the ranges are similar, with a few exceptions (Table 4.5).

Table 4.5. Onshore and offshore minimum and maximums observed for each variable across species. Note all species use the same ranges, with exceptions noted with *. Sample size n = 21.

Onshore

Elevation (m)	Slope	TPI	Rugosity	Length (km)	Width (km)	Sine Orientation	Sine Aspect
-4.24 – 12.50	0 – 52.24	-6.42 – 7.08*	1.00 – 1.43*	0.13 – 13.61	0.02 – 0.14	-0.35 – 0.35	0.33 – 1.00

Offshore

Elevation (m)	Slope	BPI	Rugosity	Sine Aspect
-26.63 – 1.80	0 – 33.37	-4.04 – 6.84	1.00 – 1.90	0.36 – 0.98

* The range for *Chelonia mydas* for TPI is -6.42 – 5.99, and for rugosity it is 1.00 – 1.38.

The beaches that contained the highest densities of nests for any of the three species (rank = high) were compared to the ranges observed in Table 4.5 (Table 4.6). For these high ranked beaches, the ranges for all the variables, except transformed beach orientation, are narrower than the ranges seen for all beaches.

Table 4.6. Onshore and offshore minimum and maximums for variables for the beaches with the highest densities of nests for any of the three species. The following beaches are included: Hobe Sound NWR, Jupiter Island, Kreusler Park, Macarthur State Park, Singer Island, and Sloan's Curve.

Onshore

Elevation (m)	Slope	TPI	Rugosity	Length (km)	Width (km)	Sine Orientation	Sine Aspect
-0.57 – 12.50	0.00 – 29.25	-2.05 – 5.99	1.00 – 1.32	0.20 – 13.61	0.02 – 0.12	-0.35 – 0.35	0.90 – 1.00

Offshore

Elevation (m)	Slope	BPI	Rugosity	Sine Aspect
-20.94 – 1.80	0.00 – 16.40	-2.24 – 1.94	1.00 – 1.18	0.66 – 0.98

Two beaches recorded no use by a turtle species for the time period included in this study: Lake Worth Municipal Beach had no recorded nesting *Chelonia mydas,* and Gulfstream Park had no recorded nesting *Dermochelys coriacea*. The variables for these two beaches were compared to the extremes of the beaches currently used by the species. Lake Worth Municipal Beach contained onshore TPI and rugosity values beyond the maximum values of nesting beaches, while offshore values were within the ranges of nesting beaches (Table 4.7).

Table 4.7. Onshore and offshore minimum and maximums compared between nesting beaches of *Chelonia mydas* and Lake Worth Municipal Beach. Variables outside the extremes of nesting beaches are shown in bold.

Onshore

	Elevation (m)	Slope	TPI	Rugosity	Length (km)	Width (km)	Sine Orientation	Sine Aspect
Lake Worth	-1.05 – 10.15	1.87 – 45.12	**-2.79 – 7.08**	**1.00 – 1.43**	0.40	0.04 – 0.05	-0.01	0.997

Offshore

	Elevation (m)	Slope	BPI	Rugosity	Sine Aspect
Lake Worth	-17.72 – -1.34	0 – 8.62	-1.19 – 0.69	1.00 – 1.03	0.98

The length of Gulfstream Park is below the extremes observed in nesting beaches for *Dermochelys coriacea* for period of the nesting years studied (Table 4.8). Offshore

values were within the ranges of nesting beaches (Table 4.8). Although the maximum offshore BPI for Gulfstream Park is on the lower end of observed values, it is still within the range.

Table 4.8. Onshore and offshore minimum and maximums compared between nesting beaches of *Dermochelys coriacea* and Gulfstream Park. Variables outside the extremes of nesting beaches are shown in bold.

	Onshore							
	Elevation (m)	Slope	TPI	Rugosity	Length (km)	Width (km)	Sine Orientation	Sine Aspect
Gulfstream Park	-1.04 – 3.17	1.95 – 32.38	-1.12 – 0.23	1.00 – 1.01	**0.13**	0.03 – 0.04	0.15	0.99

	Offshore				
	Elevation (m)	Slope	BPI	Rugosity	Sine Aspect
Gulfstream Park	-15.69 – -0.71	0 – 7.31	-0.77 – 0.56	1.00 – 1.01	0.87

4.3.2 Developing predictive models for nesting density per species

The variables obtained from the LiDAR-derived rasters were then used to model nesting density (average number of nests per km) for the three species. Stepwise multiple regressions were run to determine the best model for each species, with a balance sought between low root-mean-square error (RMSE) and Akaike information criterion (AIC) values, and high adjusted R^2 with a minimum number of variables.

Variables that were highly correlated (correlation coefficient > 0.8) were removed before model creation: onshore standard deviation of elevation which correlated with onshore maximum elevation; offshore minimum elevation which correlated with offshore average elevation; offshore standard deviation of elevation which correlated with offshore average elevation; offshore maximum rugosity with offshore maximum BPI; and onshore maximum rugosity with onshore maximum TPI. Because the pairs were so highly correlated and also so interrelated, an argument could be made for retention of either variable. For this study, the maximum and average elevations were chosen to be

retained over minimum and standard deviation, and maximum BPI/TPI measures were chosen instead of maximum rugosity values. The residuals for all models were randomly scattered above and below the y=0 line.

A model for all species was created (Table 4.9), which was able to weakly model nesting density using the mimimum elevation (OnMinEle) and the transformed orientation (SineOrient). The beta weights weights (standardized multiple regression coefficients) were similar, with the transformed orientation variable as the most influential.

Table 4.9. Multivariate stepwise linear regression results for all species combined. All beta weights are significant at $p < 0.05$. SE = standard error. Sample size n = 63.

Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
0.16	Intercept	19.75	22.29		
	OnMinEle	-21.60	12.26	0.13	-0.23
	SineOrient	-128.19	60.82	0.19	-0.28

For *Caretta caretta*, transformed orientation (SineOrient), minimum onshore elevation (OnMinEle), standard deviation of rugosity onshore (RugOnSD), and the standard deviation of TPI onshore (TPIOnSD) were able to model nesting density (adjusted R^2= 0.69) (Table 4.10). The beta weights for all four variables were similar, with the standard deviation of onshore rugosity as the most influential predictor variable as identified by the beta weight.

For *Chelonia mydas*, nesting density was modeled with onshore minimum elevation (OnMinEle), onshore maximum TPI (TPIOnMax), the standard deviation of onshore TPI (TPIOnSD), and offshore maximum elevation (OffMaxEle) (adjusted R^2=

0.61) (Table 4.10). Onshore maximum TPI and its standard deviation were the most relatively important predictor variables, with offshore maximum elevation as the least.

For *Dermochelys coriacea*, transformed orientation (SineOrient) and maximum onshore TPI (BPIOnMax) were able to model nesting density (adjusted R^2= 0.47) (Table 4.10). The beta weights showed transformed orientation influencing the model more than maximum onshore TPI.

Table 4.10. Multivariate stepwise linear regression results. All beta weights are significant at $p < 0.05$, except for onshore TPI standard deviation in the *Caretta caretta* model, which is significant at $p < 0.1$. SE = standard error. Sample size n = 21.

Response	Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
Caretta caretta	0.69	Intercept	-32.75	68.65		
		SineOrient	-300.62	90.51	0.51	-0.49
		OnMinEle	-63.68	19.75	0.63	-0.52
		RugOnSD	-4603.27	1704.45	0.69	-0.59
		TPIOnSD	313.28	166.89	0.75	0.43
Chelonia mydas	0.61	Intercept	-18.19	7.82		
		TPIOnMax	-10.01	2.53	0.07	-1.98
		TPIOnSD	106.15	29.42	0.09	1.03
		OnMinEle	-13.06	2.57	0.53	-0.75
		OffMaxEle	13.70	4.80	0.69	0.59
Dermochelys coriacea	0.47	Intercept	4.22	0.69		
		SineOrient	-9.89	2.38	0.38	-0.69
		TPIOnMax	-0.52	0.23	0.52	-0.37

4.4. Discussion

The relationships between geomorphological information and sea turtle nesting beaches have been largely restricted to a handful of beaches at a time, due to time and financial constraints. Multiple species and beach comparisons have been limited and

infrequent. The ability to compare more than twenty beaches across three species provides new insights to sea turtle nesting beaches for elevation-derived characteristics.

Sea turtle nesting activity can be successfully modeled with a small number of topographical variables, despite overall beach similarities. Therefore, as Provancha and Ehrhart (1987) and Mortimer (1982) suggested, beach characteristics, as opposed to sand characteristics, may be important factors in determining why sea turtles nest on some beaches more often than on others.

In addition, although bathymetric details have been suggested as possibly influencing nesting activity (Mortimer 1982; Provancha and Ehrhart 1987) the results from this study indicate that onshore characteristics are more influential for predicting nest density, given the variables tested. Measures of TPI, in particular, were present in all three models, demonstrating that the difference in slope of an area from the neighboring regions influences nesting activity for the three species.

Because Florida contains one of the largest *Caretta caretta* rookeries in the world and one of the largest nesting areas in the Atlantic for *Chelonia mydas* (Meylan et al., 1995), the ability to successfully model nesting density may also be repeatable with other rookeries elsewhere in these species' ranges. Although the beaches in Florida provide the only continuously used nesting area in the continental United States for *Dermochelys coriacea* (Meylan et al., 1995), it is unclear if using other more important nesting areas may provide more successful models, as these areas can support larger numbers of nesting females and may therefore show potentially different results.

The beaches included in this study have relatively narrow elevation ranges, and the inability to capture fine morphological details due to the limitations of spatial

resolution may result in the loss of potentially important information. Because of the overall similarities between the beaches, ranges for variables often overlap between beaches used by different species, and each species does not appear to prefer one extreme of the range over another. However, beaches whose ranges fall outside the established ranges are not used for nesting (e.g. Gulfstream Park for *Dermochelys coriacea*),comparing the highest ranked beaches for any species to all beaches shows narrower ranges, and the small differences present can be used to model beach use.

Elevation and elevation-based morphological details are not the only determining factors for beach use by sea turtles. Vegetation, beach use by humans including construction and beach traffic, and presence of predators are other possible influences to sea turtle nesting activity. However, the results from this study illustrate that beach physical characteristics, particularly those related to elevation, can be used to predict beach use by nesting female sea turtles.

The use of highly detailed topographical and bathymetrical data enables researchers to quickly and efficiently compare multiple study areas at once, as well as providing insights about geomorphological nuances that were not previously possible with traditional field methods, particularly in comparison to transect-based studies. LiDAR can be used to further refine known habitat requirements for species. In addition, this work highlights the potential of LiDAR to model and potentially predict habitat use for species for which coastal morphology is an important characteristic. The methods and results from this study can be applied to other species for which elevation and morphological characteristics are a limiting factor to a species' distribution. The increased spatial resolution of LiDAR, and potentially high temporal frequency (i.e. dependent on

aircraft and not satellite), allow for new research focuses for wildlife, and for those species that utilize areas susceptible to sea level rise, the need for more complete knowledge of habitat suitability requirements is of increasing importance.

Chapter 5: Measuring Effects of Morphological Changes to Sea Turtle Nesting Beaches and Nesting Success over Time

5.1 Introduction

The dynamic nature of coastal areas causes changes to beach morphology. Marine species that depend on beaches to survive have adapted to such changes, but at some point the habitat may be altered too drastically to be available as suitable habitat. Sea turtles show strong natal homing (e.g. *Chelonia mydas* (Bowen et al., 1992), *Caretta caretta* (Bowen et al., 1993)). However, individuals stray from these natal beaches (Carr & Carr, 1972; Hays & Sutherland, 1991; Tucker, 2010), indicating that fidelity to the natal beach, though strong, is not an absolute.

Entire populations may change nesting beach preferences, especially when changes to the beaches have caused the beach to become unsuitable for nesting activities. The importation of sand to artificially re-nourish beaches changes the beach morphology. The year immediately following beach nourishment, *Caretta caretta* and *Chelonia mydas* showed a decrease in nesting activity (Brock et al., 2009). Geomorphic changes, such as mud banks eroding and depositing, can result in the complete loss of sandy beaches suitable for nesting. In addition, new beaches can be created from deposition, such as that resulting from changes in river paths. In such dynamic areas, previously well-used nesting beaches can be abandoned, and other lesser-used beaches will suddenly support

large numbers of nesting *Dermochelys coriacea* females (Kelle et al., 2007). For beaches where the nesting beaches remain somewhat viable, nesting success can be affected. For a stretch of nesting beaches in Florida, post-hurricane dramatic restoration efforts (99% and 100% restoration) resulted in decreases in nesting success. These results were correlated with changes to beach profiles, in particular for slope and volume (Long et al., 2011).

Studies using LiDAR data to quantify morphological change have been completed successfully for coastal areas, particularly for highlighting post-hurricane changes to beach morphology. Pietro et al. (2008) used the difference of rasters created from pre- and post-hurricane LiDAR data in Delaware to illustrate change to Rehoboth Beach. The results highlighted areas, and direction, of loss. In addition, net beach volume change showed that in general, the beach lost sediment following the hurricane. Beach surface area and volume also differed on beaches from pre- and post-hurricane LiDAR datasets in the Archie Carr National Wildlife Refuge in Florida, as well as on beaches pre-hurricane and post-restoration (Long et al., 2011). Rasterized LiDAR data was used to chart erosion and depositional changes to Assateague Island over a span of several years. The study indicated the ends of the island experienced the most change (Zhou & Xie, 2009).

Although drastic changes to sea turtle nesting beaches have been shown to influence nesting activities, sea turtles must also face changes on a less dramatic scale. Morphological alterations to the coastal landscape occur constantly, from daily wave- and wind-caused deposition and erosion to more infrequent, but more dramatic, changes from storm and hurricane events. Nesting beaches from southern Florida were evaluated over a

time span of seven years with three LiDAR datasets from 1999, 2004, and 2006 to evaluate how these nesting beaches change and determine what, if any, effects such changes have on nesting success.

5.2 Methods

Sea turtle nesting information was procured from the Florida Fish and Wildlife Conservation Commission (2008). Each surveyed nesting beach contains information about number of nests and false crawls (nesting efforts that do not result in a nest) per species, dates of nesting activity, and the number of days and length of beach surveyed. Beaches were included in this study if surveying was conducted between 1998 and 2005 with the surveyed area of a beach varying less than 0.25 km between years, and if the number of surveying days conducted per week remained constant in order to highlight only those beaches with consistent surveying efforts. Beaches must also have been within the surveying area for the LiDAR data collection flights for the 1999, 2004, and 2006 datasets. A total of 18 beaches were included in this study (Table 5.1, Figure 5.1). Nest success was used as a measurement to evaluate suitability of each beach, with the total number of nests per beach, which represent successful crawls, divided by the number of false and successful crawls (Brock et al., 2009) for the 1999, 2004, and 2005 nesting seasons.

Table 5.1. The 18 beaches included in this study with their counties and area.

Beach Name	**County**	**Area (km^2)**
Boca Raton Beaches	Palm Beach	0.390
Deerfield/Hillsboro Beaches	Broward	0.248
Delray Beach	Palm Beach	0.338
Ft Lauderdale Beach	Broward	0.602
Golden Beach	Miami-Dade	0.109
Gulfstream	Palm Beach	0.237
Gulfstream Park	Palm Beach	0.004
Highland Beach	Palm Beach	0.016
Hollywood/Hallandale Beach	Broward	0.583
John U. Lloyd State Park	Broward	0.267
Kreusler Park	Palm Beach	0.013
Lake Worth Municipal Beach	Palm Beach	0.017
Lantana	Palm Beach	0.007
Macarthur State Park	Palm Beach	0.003
Ocean Inlet Park	Palm Beach	0.010
Ocean Reef Park	Palm Beach	0.013
Pompano/Lauderdale-by-the-Sea	Broward	0.617
Singer Island	Palm Beach	0.076
Sloan's Curve	Palm Beach	0.050

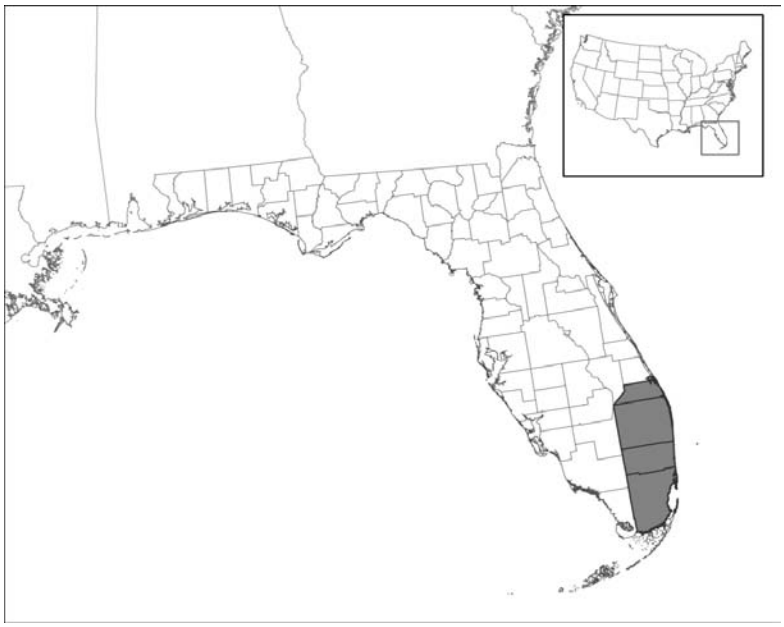

Figure 5.1. Counties in Florida that contain beaches used in this study

LiDAR data from three dates were used: 1999 data from the ATM II, 2004 from the JALBTCX using the CHARTS system, which includes topographic and bathymetric data, and 2006 from JALBTCX, also using the CHARTS system. The 1999 data had point spacings of 3.0 m, with a vertical accuracy of 15 cm and a +/- 0.8 meters horizontal accuracy. The data were collected in November of 1999, with the flight lines covering from the low water line landward to the base of the sand dunes. The 2004 data had point spacings of 3.0 m density, with the horizontal and vertical accuracy of ~15 cm root mean square error. This post-Hurricane Ivan data were collected from November to December 2004. The 2006 data had point spacings of 1.3 m density, with the horizontal accuracy of the data better than +/- 3.0m. The data were collected between December 2005 and February 2006. The JALBTCX LiDAR flights were typically conducted at low tide, (Sylvester, 2011), and the timing of all LiDAR flights allowed for covering summer accretion before winter storm erosion. The LiDAR datasets were obtained from the NOAA Coastal Services Center's Digital Coast website in UTM Zone 17 projection with NAD83 horizontal and NAVD88 vertical datum, LAS 1.1 file format.

The LiDAR data clouds were converted to rasters using the Boise Center Aerospace Laboratory (BCAL) LiDAR toolset (http://bcal.geology.isu.edulEnvitools.shtml), as described in Streutker and Glenn (2006), available as an Exelis Visual Information Solutions ENVI add-on. (To reduce the effects from outliers, points with an elevation five or more standard deviations from the median value for each dataset were removed from the data clouds.) To determine the pixel dimensions that best achieve a balance between small pixel sizes and a lack of empty cells, a ~800 m^2 area from Delray beach was compared between the 1999, 2004, and

2006 datasets at varying pixel sizes. For each dataset, rasters with spatial resolutions varying from 2 to 5 m were created, with the percentage of empty cells calculated for the sample area from Delray Beach. By the 3 m pixel size, 1 percent or less of the pixels in the sample area contained no data for the 1999, 2004, and 2006 datasets (Figure 5.2), and therefore a 3 m spatial resolution was used for all three datasets.

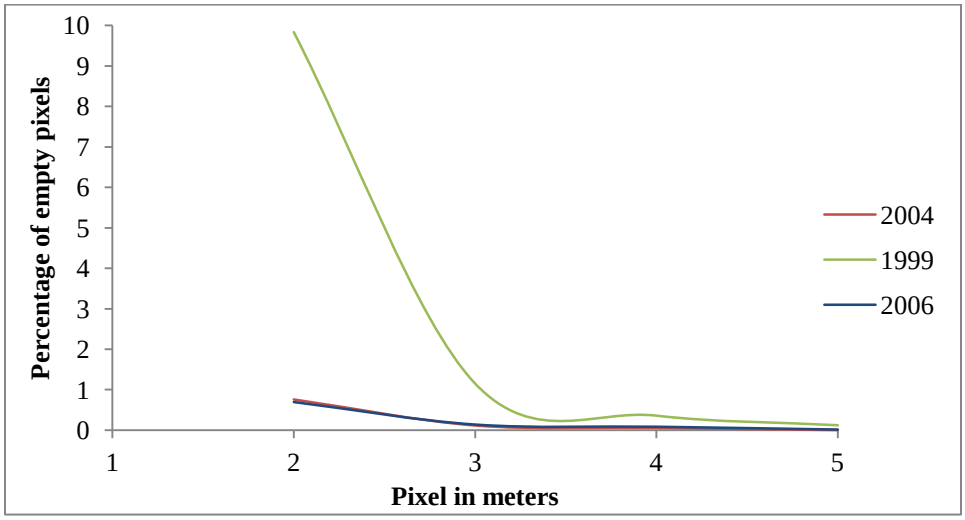

Figure 5.2. Percentage of empty pixels for varying spatial resolutions for Delray Beach.

Shoreline demarcation using the LiDAR datasets was not ideal for this study. Because LiDAR collection is done near low tide, but not at absolute low tide, it is possible that observed changes in beach areas above water across years will differ due to tidal changes and not necessarily to changes in beach areas over time. Therefore, to ensure consistent area comparisons between years, the St Johns River Water Management District (2000) dataset was used to identify the beach area, which is derived from CIR DOQQs from the USGS with a spatial resolution of 1:12,000. These orthophotos were used to create land use and land cover designations for 1999 for Florida as polygons,

which were used as the demarcation for beach areas by Long et. al (2011) to compare beaches in Florida using LiDAR data from different dates.

The elevation surfaces derived from the LiDAR data were used to obtain slope, aspect, rugosity, and TPI for the delineated beach areas. All buildings and other non-beach entities were removed from the surfaces prior to analysis. Rugosity, defined as the ratio of the surface area to the planar area (Jenness, 2011), and TPI, which illustrates a pixel's position in relation to other pixels on a surface, are often used in topographic and bathymetric studies to characterize the land and sea surfaces (e. g. (Iampietro & Kvitek, 2002; Lundblad et al., 2006; Wedding et al., 2008; Weiss, 2001). Rugosity measurements were achieved using the DEM Surface Tools for ArcGIS 9.x (Jenness, 2011), and TPI measurements with using the CorridorDesigner extension for Esri's ArcMap 9.3 (Majka et al., 2007) with the circle filter and a radius of four pixels. The volume of sand for each beach for each year was also calculated using Esri's ArcMap 9.3 Surface Volume tool.

First, changes in beach volume, the effects of volume change on slope, elevation, aspect, TPI, and rugosity, and changes to the variables themselves, were compared for all beaches to demonstrate how the beaches in the study area change over time. Linear regressions were run to evaluate the effects of elevation, slope, aspect, rugosity, and TPI as beach volume changed for the time periods 1999-2004 and 2004-2006, with the change in volume as the dependent variable. To see if certain variables observed similar changes (losses or gains) across beaches between years, the differences between 1999 and 2004, and 2004 and 2005, were compared for those variables that showed measurable differences.

Then, changes in nesting success for *Caretta caretta* and *Chelonia mydas* were compared to the changes in the variables listed above to determine if changes in nesting success can be correlated with changes in morphological changes to the beaches, with changes to nesting success as the dependent variables.

5.3 Results

5.3.1 Changes in Beach Volume and Other Variables

Some beaches lost volume for every year included in this study (Kreusler Park, Lake Worth Municipal Beach); some gained (Boca Raton Beaches, Delray Beach, John U. Lloyd Beach, Macarthur State Park, Ocean Inlet Park, Ocean Reef Park, Singer Island, and Sloan's Curve); and others fluctuated between loss and gain (Table 5.2). While the two beaches that lost volume, Kreusler Park and Lake Worth Municipal Beach, are located within 2 km of one another, there is no geographic pattern to the beaches that consistently gained volume. The amount of sand lost or gained does not correlate with transformed orientation of the beaches (for 1999 to 2004, R^2 of 0.008, not significant at $p<0.10$ significance level; for 2004 to 2005, R^2 of 0.006, not significant at $p<0.10$ significance level). All but three beaches (Gulfstream, Kreusler Park, and Lake Worth Municipal Beach) gained volume from 1999 to 2004, while an equal number of beaches lost or gained volume from 2004 to 2005.

Table 5.2. Volume of sand for each beach for each year of LiDAR data. Volume is in km^2.

Beach	1999 Volume	2004 Volume	2006 Volume
Boca Raton Beaches	0.656	0.813	0.881
Deerfield/Hillsboro Beaches	0.654	0.660	0.035
Delray Beach	0.607	0.615	0.708
Ft Lauderdale Beach	0.988	1.193	1.006
Golden Beach	0.143	0.170	0.146
Gulfstream	0.101	0.099	0.136
Gulfstream Park	0.005	0.006	0.006
Hollywood/Hallandale Beach	0.626	0.743	0.411
John U. Lloyd Beach State Park	0.268	0.275	0.284
Kreusler Park	0.040	0.035	0.025
Lake Worth Municipal Beach	0.022	0.022	0.021
Lantana	0.009	0.010	0.007
Macarthur State Park	0.134	0.199	0.265
Ocean Inlet Park	0.025	0.035	0.038
Ocean Reef Park	0.001	0.001	0.011
Pompano/Lauderdale-by-the-Sea	1.418	1.934	1.916
Singer Island	0.102	0.108	0.213
Sloan's Curve	0.040	0.053	0.079

To compare volume changes to beaches directly in the paths of hurricanes to those farther away, hurricanes in the study area that occurred between November 1999 to February 2006 (spanning the LiDAR collection dates) were mapped (Figure 5.3). Hurricane data were procured from NOAA (2009). The effects of Hurricane Ivan could be observed in the 2004 LiDAR dataset, while the effects of Wilma and Katrina could be seen in the 2006 LiDAR dataset. Hollywood/Hallandale and Golden Beaches, which were nearest the direct path of Hurricane Ivan, (categorized as an extratropical cyclone at the time of contact), showed increases in volume from 1999 to 2004. Of the beaches closest to Hurricane Wilma's path, which was an H2 at the time of contact, Singer Island

and Lake Worth Municipal Beaches also showed increases in volume, while Macarthur State Park showed a slight decrease. And for Hurricane Katrina, downgraded to a tropical storm, Hollywood/ Hallandale and Golden Beaches both showed volume decreases.

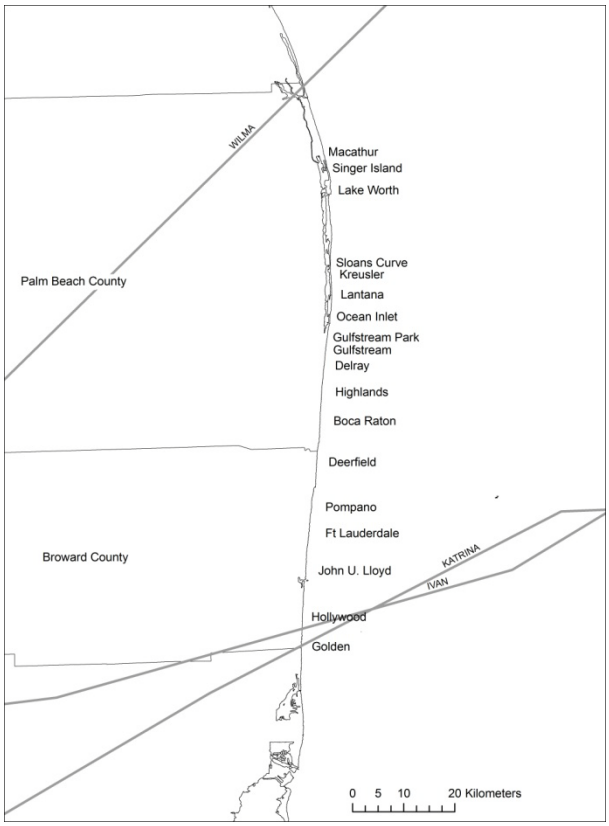

Figure 5.3. Hurricane paths and their proximity to beaches in the study area.

When comparing all beaches, the change in beach volume was correlated with the change in minimum and maximum elevation, maximum and mean slope, minimum and maximum TPI, and standard deviation of TPI and rugosity ($p<0.05$); all except mean slope and standard deviation of rugosity were significant at $p<0.01$ (Table 5.3). Although statistically significant correlations were observed, the low R^2 values show that these correlations are weak.

Table 5.3. Linear regression equations for changes in elevation-derived variables correlated to change in beach volume ($p<0.05$). Sample size n = 18.

Variable	**R^2**	**Variable coefficient**
Change in minimum elevation	0.31	-88940.26
Change in maximum elevation	0.18	44982.07
Change in maximum slope	0.21	8490.37
Change in average slope	0.13	33350.83
Change in minimum TPI	0.22	-113775.60
Change in maximum TPI	0.20	55026.90
Change in standard deviation of TPI	0.15	183321.30
Change in standard deviation of rugosity	0.16	3058584.90

The minimum elevation decreased for 90% of the beaches between 1999 and 2004, while 83% gained between 2004 and 2005. This trend of the majority of the beaches showing either a decrease or increase between years was visible for standard deviation of elevation, maximum slope, and minimum and standard deviation of TPI (Table 5.4). (Some variables, such as minimum, mean, and standard deviation of rugosity, and minimum slope were too similar between years to enable comparisons).

Table 5. 4. Comparisons of variables that showed changes between years for each beach

Beach	Aspect Mean	Aspect SD	Min Elev	Max Elev	Mean Elev	SD Elev	Max Slope	Average Slope	SD Slope	TPI Min	TPI Max	TPI SD	Rug Max
Boca Raton 99-04	-3.33	-4.36	-1.11	1.68	-0.20	0.17	12.58	-0.38	-0.49	0.22	2.15	-0.03	0.57
Deerfield 99-04	-15.81	-27.01	-0.76	0.50	-0.60	0.00	1.60	0.06	-0.24	-0.03	0.41	0.01	0.27
DelRay 99-04	-1.12	-0.46	-0.55	1.58	0.34	-0.09	9.50	-0.33	-0.21	-0.20	3.19	0.02	0.70
Ft Laud 99-04	-1.09	0.35	-0.70	1.51	0.00	0.13	20.65	1.29	1.53	-0.21	1.98	0.18	0.40
Golden 99-04	6.27	6.74	-0.32	1.42	0.10	-0.07	6.85	-0.12	1.01	-0.19	0.96	0.09	0.24
Gulfstream 99-04	-14.26	-20.37	-1.46	-0.13	-0.39	0.22	2.16	1.17	0.28	0.05	-0.68	0.12	0.00
Gulfstream Park 99-04	-29.20	-55.94	-1.02	-0.09	0.23	0.12	1.29	1.48	-0.06	-0.42	-0.07	0.10	0.04
Hollywood 99-04	-20.51	-11.82	-1.20	-0.44	-0.42	0.21	5.89	1.77	1.04	-0.61	-0.24	0.15	0.38
JuLloyd 99-04	4.11	2.98	-0.97	-0.62	-0.34	0.25	7.05	0.86	1.17	-1.54	0.01	0.10	-0.30
Kreusler 99-04	-1.60	1.92	-0.88	-0.83	-0.66	-0.09	-2.25	-0.66	0.07	-0.12	0.26	0.03	-0.04
Lake Worth 99-04	-0.64	1.12	0.05	2.20	0.20	-0.12	18.02	-0.11	2.08	-0.11	1.86	0.15	0.24
Lantana 99-04	-6.96	-18.53	-0.89	1.38	0.06	0.02	0.72	1.08	-0.06	-0.41	1.07	0.11	-0.08
Macarthur 99-04	-13.84	-23.19	-1.83	-1.04	-0.23	0.20	-11.53	1.09	-0.44	-0.09	-1.19	0.03	-0.41
Ocean Inlet 99-04	-2.60	-7.47	-1.29	-0.26	-0.48	0.16	-2.89	0.45	-0.57	0.00	-0.05	-0.02	-0.11
Ocean Reef 99-04	-4.59	-33.36	0.47	-0.19	0.61	-0.19	-2.36	-1.44	-0.87	0.01	-0.50	-0.11	-0.02
Pompano 99-04	-3.33	-3.43	-1.20	1.18	-0.07	0.00	3.64	0.22	0.30	-0.47	0.64	0.05	0.20
Singer Island 99-04	-8.80	-10.41	-0.13	1.51	0.78	0.01	4.05	-0.11	0.05	0.09	-1.37	0.02	-0.74
Sloans Curve 99-04	-26.30	-31.97	-0.85	0.67	0.16	0.21	9.19	1.67	0.12	-0.07	0.64	0.09	0.08
Boca Raton 04-05	-7.41	-10.14	0.03	-0.50	-0.03	0.01	-11.99	0.43	-0.07	-0.46	-1.27	0.00	-0.36
Deerfield 04-05	5.15	10.52	1.91	-2.40	0.96	-0.08	-12.35	-1.22	-0.76	0.69	-2.44	-0.09	-0.38
DelRay 04-05	9.97	11.76	0.73	-1.81	0.27	-0.08	-4.67	-0.11	0.27	0.22	-2.03	-0.01	-0.75
Ft Laud 04-05	-9.00	-10.78	0.70	-0.47	0.03	-0.14	-9.48	-1.34	-1.56	0.12	-1.34	-0.16	-0.20
Golden 04-05	-4.91	-4.79	0.49	-0.98	0.14	-0.07	-2.39	-0.52	-0.93	0.38	-0.34	-0.08	0.12
Gulfstream 04-05	3.39	-7.04	0.13	0.27	0.11	-0.10	-3.57	-0.07	-0.08	0.06	-0.04	-0.04	-0.02
Gulfstream Park 04-05	-0.10	-6.86	0.90	0.25	0.04	-0.01	-1.29	-0.65	-0.33	0.44	-0.04	-0.07	-0.06
Hollywood 04-05	9.99	9.53	2.32	-1.38	0.51	-0.50	-11.37	-3.18	-1.62	2.18	-1.92	-0.24	-0.45
JuLloyd 04-05	17.35	7.46	0.97	-1.38	0.58	-0.35	-11.12	-1.71	-0.75	1.37	-1.12	-0.11	-0.01
Kreusler 04-05	-3.03	-11.55	0.19	-0.45	-0.31	-0.21	2.29	0.00	0.11	0.49	-0.06	0.00	0.00
Lake Worth 04-05	-3.52	-24.26	-0.29	-2.77	-0.47	0.11	-12.74	0.68	-1.57	0.14	-2.34	-0.08	-0.34
Lantana 04-05	-2.95	-19.80	0.64	-2.49	-0.45	-0.13	-6.11	-1.10	-0.55	0.48	-1.86	-0.12	-0.01
Macarthur 04-05	9.51	15.45	0.02	0.26	-0.15	0.22	8.29	-0.06	0.76	-0.10	0.58	0.01	0.01
Ocean Inlet 04-05	-1.04	-3.80	-0.16	0.13	0.22	-0.01	0.63	0.18	-0.30	-0.04	-0.19	-0.02	0.00
Ocean Reef 04-05	20.10	36.80	-2.87	-0.65	-1.99	0.04	3.12	-1.00	0.50	0.04	0.88	-0.04	0.00
Pompano 04-05	-3.96	-4.81	0.19	-1.22	0.09	-0.03	-3.88	-0.31	-0.54	0.49	-1.86	-0.04	-0.64
Singer Island 04-05	21.02	20.79	0.02	5.09	1.83	1.64	15.07	8.03	7.05	-1.84	0.36	0.62	0.36
Sloans Curve 04-05	23.08	25.74	0.13	-0.02	0.36	-0.06	-3.72	-1.61	0.01	0.02	0.15	-0.08	-0.06

5.3.2 Change in nesting success

The change in elevation-derived variables between years was compared to change in nesting success for the 1999-2004 and 2004-2005 study periods to identify which, if any, variable changes correlate with changes in nesting success. For *Caretta caretta*, change in minimum elevation, maximum slope, and minimum and maximum TPI correlated with changes in nesting success with $p<0.05$ (Table 5.5). Changes in maximum slope were negatively correlated, indicating that greater gains in maximum slope correlated with a decrease in nesting success.

Table 5.5. Statistically significant linear regression relationships ($p<0.05$) for *Caretta caretta* change in nesting success. Sample size n = 18.

Variable	**R^2**	**Variable coefficient**
Change in minimum elevation	0.184	7.435
Change in maximum slope	0.158	-0.809
Change in minimum TPI	0.113	8.919
Change in maximum TPI	0.229	6.400

The other three variables were positively correlated. As nesting success increased over time, the minimum elevation of a beach also increased, indicating the most low-lying regions of the beach gained elevation. The greatest increase in nesting success from an earlier to a later year was also correlated with the greatest amount of increase in minimum and maximum TPI. As the minimum TPI in a beach increased, indicating the flattest areas were less flat in a later year, the nesting success also showed gains. In addition, as the change in maximum TPI increased, showing a beach contained regions that had a greater difference in elevation from the surrounding areas than the previous year, the nesting success also showed an increase between years.

For *Chelonia mydas*, only the change in mean TPI showed a correlation with change in nesting success that was statistically significant at $p<0.05$ (Table 5.6). As the change in mean TPI increased, the nesting success also increased from an earlier to a later year.

Table 5.6. Statistically significant linear regression relationships ($p<0.05$) for *Chelonia mydas* change in nesting success. Sample size n = 18.

Variable	**R^2**	**Variable coefficient**
Change in mean TPI	0.210	645.121

However, the above correlations are all weak, indicating that while changes in nesting success may be at least partially correlated with changes to some beach morphological characteristics, these changes are not wholly related to the measured variables.

5.4 Conclusion

Changes to coastal areas occur frequently, and occasionally dramatically, and all species that utilize these areas must be able to adapt to the shifting landscapes. The areas included in this study illustrated that beach volume can more than double in a span of a few years. Changes to beach volume can be weakly correlated to changes in other beach measurements, but the low R^2 values indicate that broad generalizations about the effects of beach volume changes to a beach's morphology cannot be made for this study area. Therefore, these beaches highlight that morphological changes, and their direct effects to other morphological features, need to be examined at the individual beach level.

Cyclonic activity resulted in increases in beach volume, however, the large span of time between the 1999 and 2004 LiDAR datasets make the comparisons for Hurricane

Ivan more problematic. The increases in beach volume found in this study are in opposition to Pietro et al. (2008), who found hurricanes result in loss of beach sediment. Further research to illustrate how hurricanes and other strong storms affect sea turtle nesting areas remains a priority.

Certain time periods affect the majority of the beaches in similar ways, such as decreasing maximum slope from 2004 to 2005. These changes to nesting beaches can then be correlated, albeit weakly, with changes in nesting success for *Chelonia mydas* and *Caretta caretta*. Indeed, these weak correlations observed in this study illustrate an important point: nesting success for *Chelonia mydas* and *Caretta caretta* were not wholly affected by the observed changes to their nesting beaches. These sea turtle populations are therefore able to adapt to a wide range of habitat alterations.

The ability to quantify how beaches change over time, particularly in regards to elevation-derived characteristics, is labor intensive when measured using field studies. The use of LiDAR datasets allows researchers to quickly and efficiently compare morphological details for regions across time spans, effectively enabling a researcher to collect data from the past. Linking changes to nesting success with changes in elevation, slope, and TPI creates new guidelines for potentially predicting effects to nesting after major alterations to beaches, such as hurricanes. Efforts to restore beaches to their pre-altered states to increase nesting success may be guided by research analyses similar to those included in this study.

Limitations to this research are linked to the temporal resolution of the LiDAR data available. Ideally, LiDAR flights would have been completed annually, with pre-

and post- nesting season data collected. The lack of available LiDAR for the time period 2000-2003 is a potential shortcoming, as consistent data coverage may have highlighted different effects on elevation changes to nesting success. However, as LiDAR data collection can be costly, annual data collection flights with low post spacings have the potential to be an unattainable wish for most geographic areas. Therefore, research efforts must be conducted with the data available.

Similar results were shown by Long et al. (2011) for a stretch of beaches in northeastern Florida for *Caretta caretta* and *Chelonia mydas*. The authors also illustrated that LiDAR data could be used to evaluate changes in nesting success, and that changes in beach profile, slope, and volume could be used to successfully model *Caretta caretta* nesting success. Expanding the studies to other nesting areas will allow comparisons between these Florida populations and others found globally.

Sea turtles have endured millions of years of coastal changes, but threats to their nesting habitat as a direct result of humans are a relatively new challenge. Sea level rise, in particular, has the potential to render low-lying nesting beaches unsuitable for nesting activities, and the race to obtain as much information about the effects of the environment on nesting activities is ongoing. LiDAR datasets offer new research opportunities in sea turtle, and other coastal species', research, and its full potential is still being realized. Additional studies that utilize such high resolution elevation data for habitat research may help guide management practices for these highly dynamic regions.

Chapter 6: Modeling *Caretta caretta* nesting density in Florida using elevation datasets of differing resolutions

6.1 Introduction

Sea level rise threatens the low-lying beaches sea turtles use for nesting, and entire populations may be at risk for extinction if their nesting areas are inundated (Fish et al., 2005; Fuentes et al., 2010). Female *Caretta caretta* generally nest every one to three years, with up to six years between nesting efforts recorded (Broderick et al., 2001). Although exact requirements for suitability of nesting beaches still remain unknown in the literature, aside from nesting above the high tide line in clean and relatively loose sand (Hendricksonm 1995), some populations of *Caretta caretta* appear to prefer nesting areas with higher slopes (Provancha & Ehrhart, 1987) and wider expanses of sand (Garmestani et al., 2000). *Caretta caretta* individuals generally illustrate natal homing (Bowen et al., 1993), establishing distinct populations.

Predicting habitat use with modeling efforts has been documented for many species (e.g. red squirrels (Pereira & Itami, 1991), greater rheas (Bellis et al., 2008), caribou (Tamstorf et al., 2005)), and sea turtle habitat modeling has been conducted with some success in Guantanamo Bay, Cuba (Santos (Santos et al., 2006). The aforementioned study was able to predict habitat suitability with

prediction rates of 40%, however, the habitat variable information was collected using field studies, which can be costly and time-consuming. The use of remote sensing data to create habitat models can be beneficial when large areas need to be evaluated, when cost or time is a limiting factor, or when comparisons between areas are necessary.

A possible source of DEMs with relatively high spatial resolution and a potential of more frequent data collection, particularly in comparison to satellite, is LiDAR datasets. LiDAR data are of interest for coastal studies, as they can quickly and efficiently highlight areas of change (e.g Stockdon et al. (2009), De Stoppelaire et al. (2004)). Biologists have successfully integrated LiDAR datasets into habitat modeling for a flowering annual (Sellars & Jolls, 2007), forest dwelling species (Graf et al., 2009), and coastal and estuarine areas (Chust et al., 2008).

The ability to successfully model sea turtle nesting density and predict nesting density in other areas could shed new insight to sea turtle nesting behavior. By quantifying and predicting habitat use, sea turtle researchers can be aided in future management decisions. Three elevation datasets with varying spatial and temporal resolutions will be compared for their suitability in habitat modeling for *Caretta caretta*: LiDAR-derived DEMs, and 1/3 and 1/9 arcsecond DEMs currently available from the USGS. Differences between the datasets, both for modeling and for characterizing beach habitat, will be evaluated to illustrate how the choice of elevation datasets can affect a study's results.

6. 2 Methods

Two areas on the Atlantic coast of Florida were used in this study. The variables from twenty beaches in the southern Atlantic coast established the model to predict

nesting density, and fourteen beaches in the northern and central Atlantic coast were used to test the model (Tables 6.1 and 6.2, Figure 6.1). Sea turtle nesting information was obtained from a report from the Florida Fish and Wildlife Conservation Commission (2008), which includes the number of nests for each beach per species, the length of the beaches, the number of days each beach was surveyed, and the dates of nesting activity. Only beaches with consistent surveying efforts (i.e. constant number of days the beach was surveyed for nesting activity across years) from 2001 to 2005 and with some degree of *Caretta caretta* nesting activity were considered, and of those beaches, only those with LiDAR and DEM coverage were included.

Table 6.1. Beaches used to create model

Beach Name	**County**
Boca Raton Beaches	Palm Beach
Deerfield/Hillsboro Beaches	Broward
Delray Beach	Palm Beach
Ft Lauderdale Beach	Broward
Golden Beach	Miami-Dade
Gulfstream	Palm Beach
Gulfstream Park	Palm Beach
Hobe Sound NWR	Martin
Hollywood/Hallandale Beach	Broward
John U. Lloyd State Park	Broward
Jupiter Island	Martin
Kreusler Park	Palm Beach
Lake Worth Municipal Beach	Palm Beach
Lantana	Palm Beach
Macarthur State Park	Palm Beach
Ocean Inlet Park	Palm Beach
Ocean Reef Park	Palm Beach
Pompano/Lauderdale-by-the-Sea	Broward
Singer Island	Palm Beach
Sloan's Curve	Palm Beach

Table 6.2. Beaches used to test model

Beach Name	**County**
Anastasia State Park	St. Johns
Flagler Beach SP	Flagler
Hanna Park	Duval
Mayport Naval Air Station	Duval
North Beach Club Drive	St. Johns
Old Ponte Vedra	St. Johns
Patrick Air Force Base	Brevard
Sebastian Inlet State Park	Brevard
South Beach Club Drive	St. Johns
South Cocoa Beach	Brevard
Vilano Beach	St. Johns
Wabasso Beach	Indian River
Wabasso Beach (South)	Indian River
Washington Oaks	Flagler

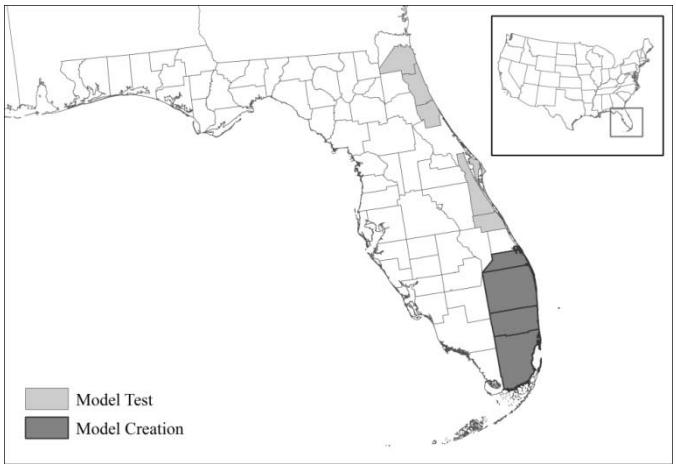

Figure 6.1. Map of study areas, showing the counties with beaches used for model creation, and the counties with beaches used for model testing.

Three elevation datasets were used. LiDAR data were obtained from NOAA Coastal Services Center's Digital Coast website in UTM Zone 17 projection with NAD83 horizontal and NAVD88 vertical datum, LAS 1.1 file format. The dataset originated from a 2006 combined topographic and bathymetric mapping project from the United States Army Corps of Engineers (USACE), and LiDAR flights were conducted by the

JALBTCX using CHARTS system. The LiDAR data flights were flown from December 2005 to February 2006, which roughly corresponds with one to two months after the nesting season of 2005 completed. Vertical accuracy is 0.30 meters within two standard deviations, horizontal accuracy is 3.0 meters within two standard deviations, and the nominal ground spacing of LiDAR samples is 2.0 meters.

To determine the optimal spatial resolution for the resulting raster dataset derived from the LiDAR, a ~ 700 m^2 area in Delray Beach and Flagler Beach State Park, which are the centrally located beaches in the model creation and model testing areas, respectively, were evaluated at different spatial resolutions. A 3.0 m spatial resolution resulted in less than 1% of the pixels containing no data, which represented the best balance between minimizing the number of no data pixels with the largest spatial resolution (Figure 6.2). With this spatial resolution in mind, the LiDAR points were first pre-filtered to remove those points with an elevation five or more standard deviations from the median value for the dataset, and the filtered dataset was converted to rasters. The filtering and raster conversion was conducted using the Boise Center Aerospace Laboratory (BCAL) LiDAR toolset, as described in Streutker and Glenn (2006), and which is available as an Exelis Visual Information Solutions ENVI add-on (http://bcal.geology.isu.edulEnvitools.shtml).

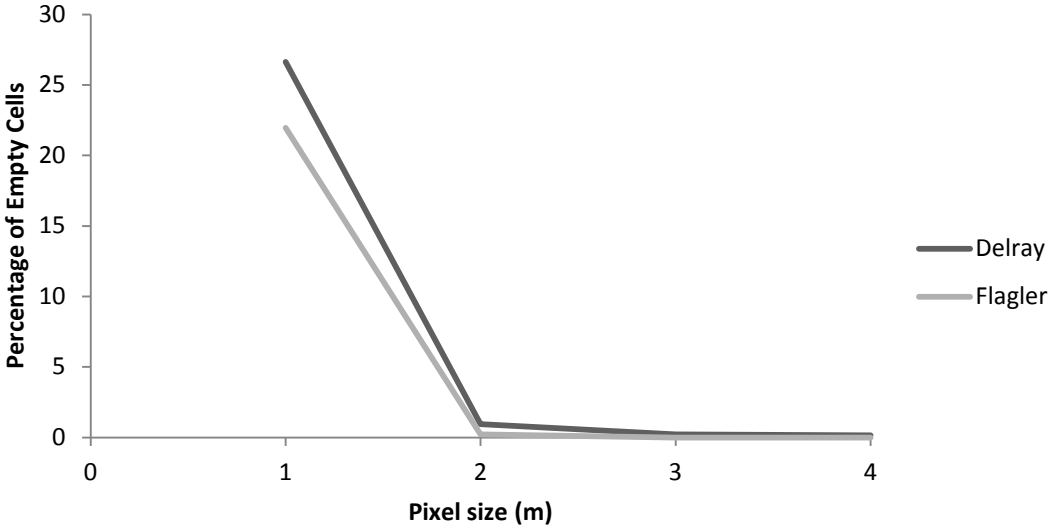

Figure 6.2. Percentage of empty cells present for each of the different raster cell sizes for Delray and Flagler beaches

In addition to the LiDAR dataset, two DEMs were obtained from the USGS NED, with spatial resolutions of 1/3 arcsecond (~10m) and 1/9 arcsecond (~3m). The 1/3 arcsecond dataset has a near-nationwide coverage, while the 1/9 arcsecond set is currently available in limited areas, including the Florida coast. The NED DEMs are derived from various source datasets, including LiDAR or digital photogrammetry. The date of acquisition also varies, with the 1/9 arcsecond DEMs ranging from February 1999 to November 2011, and the 1/3 arcsecond DEMs ranging from April 2004 to February 2010 for the study area (Table 6.3). Many of the 1/9 arcsecond dataset tiles used in this study were only recently released (February 2012), allowing for an early comparison between this dataset and the LiDAR 3 m dataset, which has been available for several years.

Table 6.3. Dates for the elevation dataset coverage for each beach

Beach	LiDAR 3 m	1/9 arcsecond	1/3 arcsecond
Anastasia State Park	Dec 2005 to Feb 2006	Feb 2008	Feb 1999 to Nov 2011
Flagler Beach SP	Dec 2005 to Feb 2006	Apr to May 2004, Mar 2006	Feb 1999 to Nov 2011
Hanna Park	Dec 2005 to Feb 2006	Mar 2007	Feb 1999 to Nov 2011
Mayport Naval Air Station	Dec 2005 to Feb 2006	Mar 2007	Feb 1999 to Nov 2011
North Beach Club Drive	Dec 2005 to Feb 2006	Feb 2007 to Feb 2008	Feb 1999 to Nov 2011
Old Ponte Vedra	Dec 2005 to Feb 2006	Feb 2007 to Feb 2008	Feb 1999 to Nov 2011
Patrick Air Force Base	Dec 2005 to Feb 2006	Sep 2007 to Jan 2008	Feb 1999 to Feb 2009
Sebastian Inlet State Park	Dec 2005 to Feb 2006	Sep 2007 to Jan 2008	Feb 1999 to Feb 2009
South Beach Club Drive	Dec 2005 to Feb 2006	Feb 2007 to Feb 2008	Feb 1999 to Nov 2011
South Cocoa Beach	Dec 2005 to Feb 2006	Sep 2007 to Jan 2008	Feb 1999 to Feb 2009
Vilano Beach	Dec 2005 to Feb 2006	Feb 2007 to Feb 2008	Feb 1999 to Nov 2011
Wabasso Beach	Dec 2005 to Feb 2006	Jul to Aug 2007, Sep 2007 to Jan 2008	Feb 1999 to Feb 2009
Wabasso Beach (South)	Dec 2005 to Feb 2006	Jul to Aug 2007, Sep 2007 to Jan 2008	Feb 1999 to Feb 2009
Washington Oaks	Dec 2005 to Feb 2006	Feb to May 2005, Feb 2007 to Feb 2008	Feb 1999 to Nov 2011

The St. Johns River Water Management District land cover and land use dataset (2004) was used to establish the landward limit for the beach areas, as implemented by Long et al (2011). The dataset is derived from color and color infrared aerial photography taken from December 2003 to March 2004, and represents land cover classes as

polygons. Because the LiDAR flights were typically conducted at low tide (Sylvester, 2011), and the timing of all LiDAR flights allowed for covering summer accretion before winter storm erosion, the shoreline was derived from the LiDAR dataset, as the breaking waves create interference which result in pixels with no data. The resulting polygons, bounded by the landward and shoreline borders, were used to extract values for each of the beaches for each of the three datasets.

For each of the elevation rasters, multiple variables were derived and extracted (Table 6.4). TPI and rugosity are additional measures of surface heterogeneity. TPI is often used to evaluate and characterize topographic and bathymetric surfaces, as it provides relational position of a pixel to its neighbors in a surface (e. g. (Iampietro & Kvitek, 2002; Lundblad et al., 2006; Wedding et al., 2008; Weiss, 2001)). Rugosity values provide the ratio of the surface to planar area (Jenness, 2011). TPI was obtained with the CorridorDesigner extension for Esri's ArcMap 9.3 (Majka et al., 2007) with the circle filter and a radius of four pixels, and rugosity with DEM Surface Tools for ArcGIS 9.x (Jenness, 2011).

Table 6.4. List of all variables collected for each beach for each elevation dataset

Variable	Measurements
Elevation	Minimum, maximum, mean, standard deviation
Slope	Minimum, maximum, mean, standard deviation
Aspect	Mean, standard deviation
TPI	Minimum, maximum, mean, standard deviation
Rugosity	Minimum, maximum, mean, standard deviation
Beach Length, Area	Total
Beach Orientation	Total

The variables listed in Table 6.4 from the LiDAR 3 m dataset were used to model nesting density (number of nests per km) from 2001-2005 for *Caretta caretta* in the southern Atlantic coast of Florida using stepwise linear regression. The average number of nests per kilometer was used as the response variable, and the variables obtained from the elevation dataset were used as the predictor variables. The best model was determined by the optimal balance between a high adjusted R^2 with the lowest number of variables and a low root-mean-square error (RMSE) and Akaike information criterion (AIC) value.

This best model was then used to predict nesting density in the northern and central Florida Atlantic coast using the elevation-derived variables from the LiDAR 3 m, USGS 1/3 arcsecond, and USGS 1/9 arcsecond DEMs. The predicted nesting density for each of the three models was compared to the observed nesting density to evaluate the effects temporal and spatial resolution have on modeling sea turtle nesting density.

6. 3 Results

6. 3.1 Habitat model creation

Highly correlated variables (correlation coefficient > 0.8) were removed before model creation (maximum TPI which correlated with maximum elevation and maximum rugosity, length which correlated with area, and standard deviation of slope which correlated with maximum slope). Tranformed orientation and minimum elevation were able to model nesting density (adjusted R^2= 0.64) (Table 6.5). The beta weights (standardized multiple regression coefficients) for the variables were similar, with transformed orientation as the most influential predictor variable as identified by the beta

weight. The residuals show the model tends to overestimate the higher and underestimate the lower densities.

Table 6.5. Multivariate stepwise linear regression results. All variables are significant at $p < 0.01$. SE = standard error. Sample size n = 20.

Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
0.64	Intercept	55.75	31.14		
	Minimum Elevation	-47.75	15.70	0.42	-0.45
	Sine Orientation	-323.28	87.36	0.68	-0.55

6.3.2 Habitat model testing

The model created using the southern beaches was then tested for the northern beaches to evaluate if sea turtle nesting density on the Atlantic coast in Florida can be predicted using the same variables. Nesting density was predicted using the orientation of each northern beach, and the minimum elevation from the LiDAR 3 m, 1/3 arcsecond, and 1/9 arcsecond elevation datasets. The intercept and the coefficients for orientation and minimum elevation were preserved for the model validation.

The model was unable to predict nesting density of the northern beaches to the same degree as the southern beaches (Table 6.6). Predicted nesting density was generally higher than actual nesting density for all elevation datasets. Correlations between the actual and predicted nesting density were weak, with R^2 values ranging from 0.07 to 0.28 (Table 6.7). The equations and R^2 values were most similar for the LiDAR 3 m and 1/9 arcsecond datasets, with the LiDAR 3 m dataset showing slightly better agreement between actual and predicted nesting density for the northern beaches.

Table 6.6. Actual and predicted nesting density (nests/km) for each of the three elevation datasets.

Beach	Actual Density	LiDAR 3 m Density	1/3 arcsecond Density	1/9 arcsecond Density
Anastasia State Park	1.22	154.11	160.01	133.29
Flagler Beach SP	12.56	222.46	217.33	188.63
Hanna Park	1.42	72.78	52.52	56.00
Mayport Naval Air Station	5.67	34.90	-6.09	7.65
Old Ponte Vedra	7.18	149.83	149.24	135.26
North Beach Club Drive	2.83	136.66	159.88	148.28
Patrick Air Force Base	170.71	143.86	117.39	138.33
Sebastian Inlet State Park	195.75	253.53	210.39	240.06
South Beach Club Drive	5.83	133.73	148.41	142.78
South Cocoa Beach	63.13	123.58	96.27	110.75
Vilano Beach	6.81	178.53	200.83	179.72
Wabasso Beach	182.65	235.29	203.67	228.50
Wabasso Beach (South)	74.62	239.52	216.13	200.06
Washington Oaks	10.18	181.13	203.10	182.22

Table 6.7. Regression equations and R^2 values for actual density against predicted density for each of the elevation datasets. Sample size n = 14.

Elevation Dataset	Regression Equation	R^2
LiDAR 3 m	y = 0.445x + 137.88	0.28
1/9 arcsecond	y = 0.4409x + 126.08	0.27
1/3 arcsecond	y = 0.2345x + 139.68	0.07

6.3.3 Comparison between predictive models for northern and southern beaches

The range of values present in the model for transformed beach orientation (-0..35 to 0.35) and minimum elevation (-5.73 to -0.70 m, mean = -1.64 m, standard deviation = 10.33 m), were different from the values present in the beaches used to test the model (northern beaches) ((orientation range of -0.47 to 0.21) and minimum elevation range of -0.98 to -0.42 m, mean = -0.77 m, standard deviation = 0.22 m)). These differences may attribute to the lower number of average nests per km for the northern beaches (52.90)

than the northern beaches (116.92). To ascertain if orientation and minimum elevation are still important to predict nesting density for the northern beaches, albeit with different coefficients and intercept for the model, additional stepwise regression models were run for each of the elevation datasets. The same criteria used in selecting the model from the southern beaches were used for the northern beach models.

For the LiDAR 3 m model, the following variables were removed before model creation due to correlations > 0.8: length (which correlated with area), mean rugosity (which correlated with mean slope and standard deviation of TPI), standard deviation of slope (which correlated with standard deviation of rugosity), maximum rugosity (with correlated with maximum slope), mean aspect (which correlated with orientation), minimum slope (which correlated with minimum rugosity), and standard deviation of TPI (which correlated with mean slope). For the 1/9 arcsecond model, length (which correlated with area), mean aspect (which correlated with orientation), standard deviation of rugosity (which correlated with maximum slope, standard deviation of slope, and maximum rugosity), and mean rugosity (which correlated with standard deviation of TPI) were removed. The variables which were removed before the creation of the 1/3 arcsecond model were length (correlated with area), maximum elevation (correlated with maximum rugosity, standard deviation of elevation, maximum slope, and minimum TPI), minimum TPI (correlated with standard deviation of elevation, maximum TPI, and maximum rugosity), maximum slope (correlated with standard deviation of elevation, minimum TPI, maximum TPI, maximum rugosity), standard deviation of TPI (correlated with mean rugosity and average slope), mean rugosity (correlated with average slope and

minimum rugosity), and standard deviation of slope (correlated with mean rugosity and maximum TPI).

For all three elevation datasets, minimum elevation and orientation were still best able to model nesting density (Table 6.8), with model adjusted R^2 values ranging from 0.41 to 0.66. The highest adjusted R^2 value resulted from the 1/9 arcsecond model. Beta weights were once again somewhat similar, with minimum elevation as the most predictor variable for all three models. The coefficient for minimum elevation was negative for the LiDAR and the 1/3 arcsecond datasets, but positive for the 1.9 arcsecond.

Table 6.8. Multivariate stepwise linear regression results. SE = standard error. Beta weights are significant at $p<0.05$ for the LiDAR 3 m and 1/3 arcsecond datasets, significant at $p<0.01$ for the 1/9 arcsecond dataset. Sample size n = 14.

LiDAR 3m

Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
0.44	Intercept	-139.38	59.78		
	Minimum Elevation	-198.56	69.95	0.27	-0.59
	Sine Orientation	-194.97	78.64	0.53	-0.52

1/9 arcsecond

Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
0.66	Intercept	107.08	26.64		
	Minimum Elevation	170.98	38.45	0.45	0.72
	Sine Orientation	-194.53	1.05	0.71	0.51

1/3 arcsecond

Model adjusted R^2	Variable	Parameter estimate	SE	Cumulative R^2 values	Beta Weights
0.41	Intercept	-83.25	44.88		
	Minimum Elevation	-185.81	70.68	0.23	-0.57
	Sine Orientation	-196.44	81.29	0.50	-0.52

6.3.4 Comparisons between the three elevation datasets

With all else being equal, one may assume that a dataset with a higher spatial resolution is preferable to those with larger pixel sizes. Disregarding temporal resolution for a moment, the values for mean and standard deviation of aspect; minimum, maximum, mean, and standard deviation of elevation; maximum, mean, and standard deviation of slope; minimum, maximum, and standard deviation of TPI, and maximum, mean, and standard deviation of rugosity were compared across the available datasets. (The values for minimum slope, mean TPI, and minimum rugosity were the same and therefore not compared.)

All of the compared variables showed the most agreement between the LiDAR 3m dataset and the 1/9 arcsecond DEM (70% or more of the beaches had more similar values for the LiDAR 3m and the 1/9 arcsecond DEM), except for minimum elevation and standard deviation of rugosity (Table 6.9). For minimum elevation, five of the beaches had the greatest agreement between the 1/9 and 1/3 arcsecond DEMs, and six beaches had the greatest agreement between the LiDAR 3m dataset and the 1/9 arcsecond DEMs. Similarly, for standard deviation of rugosity, three of the beaches had the greatest agreement between the 1/9 and 1/3 arcsecond DEMs, and three of the beaches had the greatest agreement between the LiDAR 3m dataset and the 1/9 arcsecond DEMs. Compared to the LiDAR 3m dataset, the 1/3 and 1/9 arcsecond DEMs did not consistently over or underestimate values for the compared variables.

Table 6.9. For each beach in the northern study area, the values for beach variables are given for each of the three elevation datasets: LiDAR 3 m, 1/9 arcsecond (1/9 in table), and 1/3 arcsecond (1/3 in table) DEMs.

Source	Beach	Aspect Mean	Aspect SD	Min Elev	Max Elev	Mean Elev	SD Elev	Max Slope	Average Slope	SD Slope	TPI Min	TPI Max	TPI SD	Rug Max	Rug Mean	Rug SD
LiDAR	Anastasia State Park	107.39	76.78	-0.79	6.44	1.34	1.27	23.98	2.20	2.75	-1.88	1.85	0.18	1.17	1.003	0.008
1/9	Anastasia State Park	102.75	69.55	-0.91	7.69	1.35	1.44	26.89	2.71	3.16	-1.98	2.14	0.22	1.14	1.004	0.010
1/3	Anastasia State Park	107.47	114.04	-0.35	4.58	0.77	0.85	8.63	0.43	0.93	-1.84	1.55	0.18	1.02	1.000	0.001
LiDAR	Flagler Beach SP	68.84	13.97	-0.96	5.54	0.97	1.08	18.02	6.08	2.32	-0.78	1.47	0.33	1.05	1.009	0.005
1/9	Flagler Beach SP	68.68	10.62	-0.86	4.92	1.62	0.81	12.04	4.61	1.64	-0.82	1.12	0.26	1.02	1.004	0.003
1/3	Flagler Beach SP	67.08	9.77	-0.26	4.15	1.59	0.63	5.60	2.35	0.98	-1.42	1.91	0.53	1.01	1.002	0.001
LiDAR	Hanna Park	127.68	74.50	-0.89	5.68	1.58	1.50	19.76	4.12	3.53	-1.00	1.71	0.26	1.09	1.006	0.010
1/9	Hanna Park	128.77	74.76	-0.47	5.68	1.94	1.29	23.57	4.59	3.69	-0.89	1.82	0.29	1.11	1.008	0.013
1/3	Hanna Park	79.88	107.38	-0.54	2.13	0.07	0.33	4.69	0.35	0.88	-0.50	1.22	0.18	1.00	1.000	0.001
LiDAR	Mayport Naval Air Station	113.29	42.84	-0.98	5.31	0.78	1.40	17.24	3.15	2.65	-0.89	1.33	0.16	1.06	1.003	0.006
1/9	Mayport Naval Air Station	118.11	49.35	-0.12	5.27	1.36	1.14	25.58	4.10	3.79	-0.99	1.51	0.28	1.12	1.008	0.015
1/3	Mayport Naval Air Station	12.66	51.63	-0.41	1.07	0.01	0.09	3.10	0.08	0.33	-0.39	0.77	0.07	1.00	1.000	0.000
LiDAR	Old Ponte Vedra	113.14	75.80	-0.42	5.06	1.71	1.17	16.58	4.23	3.12	-0.52	1.14	0.24	1.07	1.006	0.009
1/9	Old Ponte Vedra	82.95	30.06	-0.76	4.70	1.45	1.40	20.45	5.04	3.74	-0.64	1.51	0.28	1.08	1.008	0.011
1/3	Old Ponte Vedra	81.23	42.89	-0.47	2.00	0.54	0.57	4.40	1.69	0.88	-0.63	1.31	0.39	1.00	1.001	0.001
LiDAR	North Beach Club Drive	87.87	44.66	-0.50	5.17	1.92	1.44	17.61	5.18	3.12	-0.50	1.70	0.23	1.06	1.008	0.010
1/9	North Beach Club Drive	100.16	66.21	-0.63	4.31	1.65	0.89	15.81	3.59	2.70	-0.86	1.19	0.23	1.05	1.004	0.005
1/3	North Beach Club Drive	91.98	115.99	-0.39	8.57	0.98	1.68	11.28	0.83	1.61	-2.29	2.26	0.22	1.02	1.001	0.002
LiDAR	Patrick Air Force Base	85.62	27.29	-0.95	6.32	1.64	1.50	18.10	4.78	2.61	-0.55	1.75	0.21	1.07	1.005	0.005
1/9	Patrick Air Force Base	86.97	32.20	-0.39	5.59	1.87	1.30	19.90	4.65	2.74	-0.82	1.74	0.25	1.07	1.006	0.007
1/3	Patrick Air Force Base	72.58	62.84	-0.83	2.78	0.52	0.73	6.52	1.53	1.40	-1.13	1.60	0.43	1.01	1.001	0.001
LiDAR	Sebastian Inlet State Park	67.93	35.26	-0.98	3.36	1.25	1.05	12.03	4.74	2.48	-0.66	0.79	0.23	1.02	1.006	0.004
1/9	Sebastian Inlet State Park	71.10	35.36	-0.07	3.40	1.83	0.89	14.74	4.23	2.95	-0.89	0.74	0.26	1.04	1.006	0.006
1/3	Sebastian Inlet State Park	107.11	92.34	-0.69	2.06	0.03	0.36	5.23	1.07	0.90	-1.04	1.53	0.31	1.00	1.001	0.001
LiDAR	South Beach Club Drive	84.92	40.60	-0.51	4.94	1.70	1.24	17.95	4.87	2.97	-0.61	1.67	0.24	1.06	1.007	0.009
1/9	South Beach Club Drive	88.90	48.13	-0.82	4.73	1.39	1.03	22.16	4.41	3.53	-1.00	1.92	0.31	1.09	1.006	0.010
1/3	South Beach Club Drive	83.95	53.05	-0.70	5.24	1.41	1.08	9.01	2.84	1.49	-1.77	2.65	0.67	1.01	1.002	0.002
LiDAR	South Cocoa Beach	113.36	68.42	-0.95	4.94	1.59	1.10	14.91	2.94	1.99	-0.58	1.48	0.14	1.07	1.002	0.003
1/9	South Cocoa Beach	114.06	69.67	-0.38	5.87	1.85	0.89	20.15	2.95	1.83	-0.56	2.02	0.15	1.08	1.002	0.002
1/3	South Cocoa Beach	54.56	65.03	-0.68	3.21	0.25	0.53	7.05	1.06	1.40	-0.98	2.15	0.34	1.01	1.001	0.001
LiDAR	Vilano Beach	85.21	51.18	-0.48	4.93	1.85	1.02	19.10	5.29	2.95	-0.73	2.16	0.32	1.13	1.007	0.007
1/9	Vilano Beach	91.64	58.58	-0.95	4.88	1.51	1.11	14.74	14.74	2.95	-1.02	1.94	0.24	1.05	1.004	0.004
1/3	Vilano Beach	95.77	77.22	-0.51	5.08	2.79	1.63	7.09	1.79	1.38	-1.66	1.72	0.44	1.01	1.002	0.002
LiDAR	Wabasso Beach	74.73	43.38	-0.89	4.78	0.99	1.06	18.19	4.63	2.84	-0.69	1.79	0.27	1.11	1.006	0.006
1/9	Wabasso Beach	82.07	58.59	-0.23	4.92	1.52	0.96	21.40	4.24	2.96	-1.11	1.85	0.29	1.08	1.005	0.006
1/3	Wabasso Beach	86.63	68.85	-0.75	5.48	2.22	1.29	10.35	2.85	1.74	-2.74	2.65	0.72	1.02	1.002	0.002
LiDAR	Wabasso Beach (South)	62.73	7.30	-0.80	3.40	0.29	0.71	17.50	4.49	2.26	-0.36	1.62	0.27	1.05	1.005	0.004
1/9	Wabasso Beach (South)	73.53	46.60	-0.31	3.58	0.90	0.62	10.91	3.79	2.03	-0.53	1.25	0.25	1.02	1.004	0.003
1/3	Wabasso Beach (South)	64.60	36.09	0.03	4.89	1.89	1.15	8.99	3.86	1.67	-2.07	2.30	0.91	1.01	1.007	0.004
LiDAR	Washington Oaks	70.75	14.88	-0.50	4.15	1.53	1.11	15.34	7.05	2.76	-1.10	1.21	0.39	1.05	1.013	0.007
1/9	Washington Oaks	71.32	17.57	-0.96	3.22	1.25	0.96	14.49	6.02	2.26	-1.18	0.96	0.34	1.04	1.008	0.004
1/3	Washington Oaks	69.00	7.33	-0.52	2.56	1.02	0.79	7.02	3.50	1.12	-1.45	1.39	0.75	1.01	1.005	0.001

6.4 Discussion

The relatively large geographic area evaluated in this study for modeling and predicting sea turtle nesting density illustrated that the *Caretta caretta* populations on the Atlantic coast of Florida share similar habitat requirements. Minimum elevation and orientation of nesting beaches can explain a large amount of the variability seen across nesting beaches. These two variables resulted in successful models for both study areas, the northern and southern beaches, and across three different elevation datasets: LiDAR 3 m, 1/9 arcsecond, and 1/3 arcsecond DEMs. However, using the model from the southern beaches to predict nesting density for the northern beaches was unsuccessful. The weak correlations between predicted and actual nest density for these beaches across all elevation datasets highlights an important distinction. The morphology of a beach may help determine nesting density, but the exact requirements for the morphological details appear to vary across geographic areas.

Therefore, this study illustrates that differences between beaches used by different nesting populations of *Caretta caretta* can affect nesting density, and that determining factors for nesting density for one geographic area do not necessarily dictate nesting density in another area to the same extent. Despite the differences seen between the two geographic areas, it is important to note that the same two variables can be used to model nesting density, showing there is a large amount of similarity between the northern and southern study areas. Because Florida houses one of the largest *Caretta caretta* rookeries in the world (Meylan et al., 1995), expanding the geographic extent of this study to other rookeries found in the United States and worldwide would yield results of interest. Do

minimum elevation and orientation successfully model nesting density for other beaches, or do other variables have more of an impact?

A potential shortcoming to the study is the derivation of the shoreline from the LiDAR dataset, as the LiDAR flights were conducted at low tide, but not necessarily at absolute low tide due to logistical constraints (i.e. weather-related). It is also important to note the sign of the coefficients for minimum elevation in the models. The coefficient for the 1/9 arcsecond model was positive, while the coefficients for the other models were negative. Although all models included minimum elevation, this difference in coefficient sign illustrates that the choice of elevation dataset can influence the direction of relationships observed.

It was fortunate that the study areas were covered by several elevation datasets: LiDAR coverage from the CHARTS system, and DEMs available from the USGS. Comparisons between these three datasets highlighted that different results are obtained depending on which dataset is used. Because both the USGS DEMs incorporated data from a wide range of years (February 1999 to November 2011 for the 1/9 arcsecond set, and April 2004 to February 2010 for the 1/3 arcsecond set) for the area of interest, direct comparisons regarding differences in spatial resolution are made more difficult. However, even with such temporal differences, the elevation datasets with the most similar spatial resolutions (LiDAR 3 m and the 1/9 arcsecond DEM) resulted in values for the measured variables that were more similar than the LiDAR 3 m and the 1/3 arcsecond DEM, or the 1/3 and the 1/9 arcsecond DEM, for the majority of the beaches and all but two of the compared variables. Therefore, it appears that even though the data

collection window was narrower for the 1/3 arcsecond dataset, the finer spatial resolution of the 1/9 arcsecond dataset was able to capture more similarities of the beach landscapes than the 1/3 arcsecond dataset, when compared to the LiDAR 3 m surfaces. These results suggest that spatial resolution may be more important to beach morphological characterization than temporal resolution, if a choice must be made, and if major morphological changes have not occurred. Ideally, of course, datasets with low spatial resolution and frequent data collection would be available for one's area of interest, and such trade-offs would not need to be considered.

It is important to note that because all three elevation datasets were able to model nesting density for the northern beaches, it is tempting to say that the 1/9 arcsecond dataset model is the most "true," based on its higher R^2 values. However, because of the temporal differences of the datasets, no one model can be considered necessarily better than the others. One caveat is that nesting density was averaged across five years, and so none of the datasets can show how the nesting density for each individual year was affected by the differences in the beaches. Instead, the LiDAR 3 m dataset is considered a snapshot of the last year of the nesting density averaging period, and the 1/9 and 1/3 arcsecond datasets are pieced together from many different years. Therefore, the conclusions one can draw from the results of this study are not that the 1/9 arcsecond is the best choice for modeling nesting density, but rather that all three datasets showed similarities in the most correlated variables with nesting density, and the 1/9 arcsecond and LiDAR 3 m datasets generally agree more than with the 1/3 arcsecond DEM (with an exception of minimum elevation, explaining the similarities between the LiDAR 3 m and

the 1/3 arcsecond models). When the collection date is of importance, especially when multiple years need to be compared, the LiDAR datasets are unparalleled. However, the 1/9 arcsecond dataset may be useful for other studies, especially due to the its similarities with the LiDAR 3 m dataset and its relative ease of use (no processing required). As more of the 1/9 arcsecond dataset from the NED is released to the public, its use will likely become more widespread.

The results from this study identify several topics and considerations for future studies. Aside from expanding the geographic area to other nesting beaches to determine if the variables correlated with nesting density are similar elsewhere, the methods could be applied to other sea turtle species found worldwide. Other coastal species for which elevation is a limiting factor to habitat use may also benefit from habitat studies incorporating fine spatial resolution data. And finally, the use of this fine spatial resolution data for characterizing elevation-derived beach features should be incorporated whenever such data is available, as coarser resolution data may yield different results.

Chapter 7: Conclusions

Nesting density, which is the major component of sea turtle habitat use on land, is at least partially correlated to elevation and morphological features of beach landscapes for the Atlantic coast of Florida.

The overarching result from this dissertation is a major contribution to sea turtle research, particularly in regards to studies focusing on nesting beaches. Although other researchers in the past have surmised elevation has a role (Mortimer, 1982), or found that slope may help determine nest placement (Provancha & Ehrhart, 1987; Wood & Bjorndal, 2000), the studies found herein represent the first attempt at quantifying nesting density for multiple sea turtle species, across a relatively large geographic range, using solely morphological variables.

This relationship between nesting density and beach elevation characteristics was observed for all three species from this study: *Caretta caretta*, *Chelonia mydas*, and *Dermochelys coriacea*. Because the beaches of Florida contain one of the largest *Caretta caretta* rookeries in the world and one of the largest nesting areas in the Atlantic for *Chelonia mydas* (Meylan et al., 1995), it is possible that such relationships are present elsewhere in these species' ranges. In addition, the only continuously used nesting area in the continental United States for *Dermochelys coriacea* is in Florida (Meylan et al., 1995), which indicates that the Florida beaches are more suitable than other beaches in the area, possibly due to these correlations.

Although these three species largely nest on the same beaches, albeit in different numbers, some differences in beach requirements were observed. *Chelonia mydas* and *Dermochelys coriacea* showed no nesting activity for those beaches with variables that fall outside of the range of observed values. This distinction highlights that sea turtles do not use the beaches in Florida simply because they are available. Instead, the sea turtles do appear to have preferences in terms of beach suitability.

Conversely, bathymetric details did not aid in modeling nesting density for *Caretta caretta* or *Dermochelys coriacea*, and offshore variables were not the main contributor to nesting density models for *Chelonia mydas*. Therefore, although offshore features and approach had been theorized as affecting nesting activity (Mortimer, 1982; Provancha & Ehrhart, 1987), the results from this study showed that offshore morphology does not have as much of an effect as onshore details when investigating nesting density for any of the three species.

Because most previous sea turtle nesting studies focus on small geographic areas, often during a limited time frame (largely due to time and financial constraints), comparing large areas to one another is rarely done. For *Caretta caretta*, relationships seen in southern Florida, in terms of modeling nesting density with minimum elevation and orientation, were similar in northern and central Florida, as these two variables also correlated with nesting density for those beaches. This similarity indicates that sea turtle populations across large areas may share similar nesting requirements. However, because the intercept and coefficients differed for the two models, it shows that perhaps slightly different nesting constraints are present across geographic areas.

In addition to comparing large geographic areas, this study also sought to compare nesting areas between years. Beaches are dynamic. Thus, how these beaches change over time, and how these changes affect nesting success, were evaluated. Southern Florida beaches did not show a consistent pattern when evaluating beach volume gains or losses for the predetermined areas, as some beaches gained volume, and others lost. Changes in volume were weakly correlated with changes in some morphological variables (highest R^2 of 0.31, $p<0.05$). While some variables showed a correlation between their change and the change in nesting success, relationships were not strong (highest R^2 of 0.23, $p<0.05$). Although the R^2 values observed from this study were not high, the ability to relatively quickly compare changes over time to beach areas and compare these changes to nesting success represented a gap in the current literature for this study area. In addition, because these changes were not strongly correlated with nesting success, it highlights the resilient nature of nesting sea turtles. Apparently, the observed changes were not drastic enough to dramatically affect nesting success, which documents the tolerance of sea turtles for natural beach change.

The use of beaches as the unit of study instead of considering the sites directly surrounding nests is not commonly seen in sea turtle studies. The reason for the traditional use of nest site surroundings is mainly due to the choice of scale of the study. When one is focusing on a single beach, or a few neighboring beaches, it makes more logistical sense to solely look at immediate nest surroundings. In addition, when a researcher wants to evaluate why a particular sea turtle individual chose a nest site, and how this nest site affects the developing young, the site itself is the important factor.

Conversely, this study sought to compare nesting populations, and not the individual sea turtles themselves. Because individuals have been the focus of many studies in the past, and few concrete generalizations can be made regarding nesting sites across species despite decades of study, there was a conscious choice to change the scale of the study to the population level. By comparing multiple beaches at once, the researcher is able to visualize patterns not previously possible with single beach studies conducted at different time scales using different methods.

Because of the paltry number of sea turtle papers that have results regarding nesting beach characteristics, sea turtle studies often combine species when describing nest site characteristics, or use the results from one beach area to generalize the sea turtle species as a whole. This expansion of the results from one study to be considered indicative of the species in the entire geographic area is a common practice for some ecologists. Termed transmutation (O'Neill, 1979), the errors associated with constructing inferences from studies conducted at a fine scale to a much broader scale has been ignored by many ecologists (Wiens, 2002). Comparisons of large geographic areas across species at once can, at least in part, help assuage these issues.

The methods of this study were largely reliant on fine-scale data with collection dates falling near the nesting season. The relatively recent availability of free and low-cost LiDAR data was important to the development of this research. Aside from these LiDAR datasets, elevation data is commonly coarse-scale and with less desirable temporal resolution. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) global digital elevation map (GDEM), which is also free with a

near-global coverage, has a spatial resolution of 30 m and a vertical accuracy of 25 m. Shuttle Radar Topography Mission's (SRTM) data is free with near-global coverage with a similar spatial resolution to ASTER, and a slightly better vertical accuracy of 10 m. Even without considering temporal resolution, the spatial resolution alone is much coarser than the LiDAR datasets available.

Therefore, a possible alternative to the LiDAR datasets were the DEMs from the USGS NED. The 1/9 arcsecond dataset has a spatial resolution similar to the rasterized LiDAR from chapters 4 and 5, and the 1/3 arcsecond dataset is still at a finer spatial resolution than the ASTER GDEM or SRTM datasets (ca. 10 m). Indeed, there were similarities observed between the LiDAR dataset and the 1/9 arcsecond DEMs, more so than with the 1/3 arcsecond dataset. In addition, all three datasets highlighted minimum elevation and orientation as able to model nesting density, albeit with slightly different equations. However, because of the temporal differences between the LiDAR datasets (a time span of a few weeks for the study area) versus that of the DEMs (years to cover the study area), the incomplete 1/9 arcsecond data coverage, and because multiple LiDAR datasets are available to compare different years, the LiDAR was still clearly a more suitable choice for this study.

The overarching theme to this dissertation is the importance of scale to habitat studies. Sand grain studies, and other research that focused on the habitat directly surrounding nests, could only result in a limited scale due to the results. Expanding the results from one beach to the rest of the sea turtle population, or even to the species level, should not have been done, but as shown earlier, was often performed by ecologists due

to the limited number of studies with positive results. Therefore, expanding the scope of sea turtle studies from sand grains to large geographic areas provides two benefits: one, large scale studies allow broader generalizations to be formed, and two, new insights can be discovered.

The results of the three studies in this dissertation highlight the importance of the field of geography to ecologists. Considering the scale of studies and addressing transmutation are key issues that geographers can provide to sea turtle researchers, in particular. Sand grain studies have only taken the research so far, and the necessity for new scopes of research is paramount. Without this push to encompass broader research scales, the stagnation of sea turtle research is inevitable.

Prior to this dissertation, a major gap in the sea turtle literature existed: a lack of broad-scale, multi-beach studies; a lack of comparisons of morphological details, both on and offshore; and a lack of addressing how beaches changed over time and how this affected nesting success. Without attempting to fill this gap, sea turtle researchers were operating with a large piece missing from the puzzle of sea turtle natural history. This dissertation has not only begun to fill this gap, it has also provided the methodology for future research, as well.

7. 1 Hypotheses testing

This study was designed to test three hypotheses regarding the nesting beaches of Atlantic Florida sea turtles and their possible relationships to nesting density. Each hypothesis will be addressed separately below.

Hypothesis 1: Morphological features such as offshore approach, beach slope, and slope change are related to sea turtle nesting preference by species. In addition, each species will have a range and degree of acceptability for different morphological features which can be quantified.

The results of chapter 4 address this hypothesis. Sea turtle nesting density is related to a handful of morphological beach characteristics, which vary for each species. For *Caretta caretta*, these variables are orientation, minimum onshore elevation, standard deviation of rugosity onshore, and the standard deviation of TPI onshore. For *Chelonia mydas*, they were nesting onshore minimum elevation, onshore maximum TPI, the standard deviation of onshore TPI, and offshore maximum elevation, and for *Dermochelys coriacea*, minimum onshore TPI and orientation contributed. The models used average nesting density from 1998 to 2005.

Due to the three different species utilizing roughly the same beaches, the range for the variables largely overlapped, with a few differences. The beaches not used by *Chelonia mydas* and *Dermochelys coriacea* did show values outside the established ranges for some variables. The degree of acceptability for each species, represented as the range for each variable for the different degrees of use (high, medium, and low), overlapped for most variables, illustrating that a beach with a high degree of use does not have a narrower range for a variable than a beach with a low degree of use. In other words, the range and degree of acceptability can be quantified, but a large amount of overlap between species and among species for variables existed.

Hypothesis 2: Sea turtle nesting beaches change physically over a period of time, and these changes can reflect fluctuations in sea turtle nesting success. Some morphological features are more prone to change than others.

As seen in chapter 5, the changes in sea turtle nesting beaches can be quantified, and changes to sea turtle nesting success can be correlated, at least in part, with changes to the nesting beaches. The changes observed in beach volume are not correlated with beach orientation, and some changes in volume can be weakly correlated to changes in other morphological characteristics. In addition, the physical changes to the beaches in terms of volume are not uniform across all beaches for the study years, indicating that even neighboring beaches can show differences in volume changes for the same time period. However, the changes to some beach characteristics do show similar trends for the majority of beaches across a time span, such as most beaches showing a gain in volume from 1999 to 2004, and a decrease in maximum slope from 2004 to 2005. All of the above results illustrate the changing environment of sea turtle nesting beaches. Some changes to these variables, such as the change in maximum slope, can be correlated with sea turtle nesting success.

Hypothesis 3: The results of hypotheses 1 and 2 integrate with current issues of data and scaling for sea turtle research, and the inclusion of new remote sensing data improve the predictive quality of habitat models. This hypothesis will be addressed by investigating if sea turtle nesting habitat predictions change with the addition of other remote sensing data sources.

The results from chapter 6 show that a predictive model using LiDAR datasets with a spatial resolution of 3 m for southern beaches does not predict nesting density well for northern and central beaches. The southern model overestimated nesting density for the more northern beaches. This trend was seen for both the LiDAR 3 m dataset, and the 1/9 and 1/3 arcsecond NED datasets. However, the regression equations and R^2 values for actual density against predicted density for the LiDAR 3 m and the 1/9 arcsecond were similar, indicating that the LiDAR dataset and the 1/9 arcsecond DEM, which is produced from earlier LiDAR datasets, are more similar than these datasets with the 1/3 arcsecond DEM. This similarity was also seen when comparing values for the different morphological characteristics across the three datasets, except for a few variables, most notably minimum elevation.

Most importantly, chapter 6 highlighted that no matter the elevation dataset utilized, two variables were consistently able to model nesting density: minimum elevation and orientation. The differences between datasets instead were seen in R^2 values and variable coefficients. These similarities show that different elevation datasets may result in similar habitat modeling efforts, which may be encouraging for study areas for which there is only one choice.

7.2 Drawbacks

The main potential drawback to this study is that of data collection dates. While the LiDAR dates coincided with the end of the nesting seasons, it would have been ideal to have had LiDAR collection dates in the middle, when nesting activity is at its peak. The end of nesting season may not capture what the majority of female sea turtles were

experiencing on the beach while searching for a suitable nesting site. Of course, ideally, LiDAR collection dates at the beginning, middle, and end of nesting season would have been wonderful to capture how the nesting areas change over a season. (Although this would have resulted in three times the amount of data processing, and many more gigabytes of data storage.)

To continue on this path of wishes, LiDAR data collection every year, three times a year during the nesting season, would have captured nuances that may have been lost in the years between the existing data collection. What happened to the morphology of the nesting beaches in 2001? 2003? Without LiDAR data collection, these years are now lost.

The studies found herein focused on the beaches as the units of study, instead of the microhabitats directly surrounding nests. This switch from the micro-scale to the macro-scale has provided new insights to sea turtle natural history. However, there are still studies that need to be conducted at a single beach level – particularly those regarding false and successful crawls. The location and length of false crawls can provide information about the suitability of a beach which to date has been largely ignored in the literature. If false crawls largely occur in the same region of a beach, are there disturbances or unsuitable areas of the beach that cause the unsuccessful nesting attempts? Do different species have their false crawls in different areas of the beach? The change in the scale of studies can provide information about nesting behavior that is still lacking in the literature.

Researchers have suggested that beach morphological features are correlated to nesting density, and this possibility was explored in this dissertation. However, there are

other factors that could be causing nesting density differences in beaches. The smell of the beaches or the effects of water currents may also affect sea turtle nesting behavior, and further research could uncover other insights.

Of additional concern is the drawback to any habitat modeling study – is what I am seeing, and what the datasets are telling me, actually what is happening? Are the correlations with elevation causing these observed differences in nesting density, or are they simply correlations? Are there additional variables, perhaps even more influential, that have been missed? These nagging concerns segue nicely to…

7. 3 Future studies

Although the results of this study fill a gap in sea turtle literature, they also spawn more questions. Do these trends hold true across all nesting areas? For all species? The ever-pressing need and battle cry for more studies, more species, more areas holds just as true for sea turtles as it does for nearly any other research topics.

The use of LiDAR datasets has helped to answer a small piece of the sea turtle puzzle, at least for the Atlantic coast of Florida. Twenty, or even ten, years ago, such research was nearly impossible. In areas where LiDAR is not and may not be available, the 1/9 arcsecond USGS NED DEM may be able to fulfill similar research goals for the United States, once it has been more widely released. However, many sea turtle nesting areas found throughout the world face more imminent problems than simply not being covered by LiDAR collection projects.

Sea level rise, rising temperatures that skew sea turtle gender ratios, beach construction, increased predation by domestic dogs, sand harvesting, nest trampling-

these threats, among countless others, threaten the livelihood of sea turtles today. Many of these threats were unknown when sea turtles first evolved to their present forms, and the increasing threats by humans may eradicate these species before they are able to cope with the current conditions. As trite as it may seem, there is a race in sea turtle research, just as there is pressure for other coastal species researchers, and any additional insights to their habitat needs may help ensure the future of these much beloved creatures.

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